

UTRECHT UNIVERSITY

Department of Information and Computing Science

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**Proposal - Master Thesis - Artificial Intelligence**

**Rhythm and Reason: Adding fine-grained control to deep learning  
music generation models.**

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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 LastMinuteGig, a Musical Attention Control Training (MACT) application for Parkinson's patients. To maintain engagement and the effect of the intervention, a diverse set of controlled, adaptive music is needed. Advances in generative music offer a scalable solution. This research 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 MusicLang, a transformer based music generator, which will be used to build musical assets for LastMinuteGig.

## Contents

# 1. Introduction

Music is a cornerstone in modern video games. Music evokes emotional responses, triggers memories, can direct attention and improve immersion and the overall experience of a game. Yet, it is not uncommon for players to become disengaged from the game music, often due to excessive repetition or simply different personal preferences. Rogers and Weber, 2019 This can be a problem in serious games for therapeutic use such as “Last Minute Gig” a gamified Musical Attention Control Training (MACT) application, aimed to improve attention control in patients with Parkinson’s disease Chalkiadakis, 2022. Ideally MACT is a personalized experience with dynamic adjustments taking into account a patient’s abilities and preferences. In the context of gamified self-directed therapy, this is crucial to keep patients engaged and progressing.<sup>1</sup> In order to accommodate a wide array of patient’s abilities and preferences in a MACT-game, a considerable amount of musical material, specifically music that fits the constraints of MACT is required. One potential avenue to provide this is through controlled music generation.

Over the last years, music generation has grown from a mostly academic endeavor to a billion-dollar industry. Large technology companies are exploring music generation with foundation models such as Meta’s MusicGen Copet et al., 2023 or Google’s MusicLM Agostinelli et al., 2023. The commercial startup Suno is valued at 500 million dollars, while chart-topping songs are being generated with Udio Ferdinand Meyen, 2024 Stassen, 2024. This breakthrough is powered mostly by advances in language modelling, bringing about Large Language Models such as GPT-4 or LLAMA3 applied to music.

In the context of 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 game-play and branching story lines. When additional complexity is added to adapt the music to individual preferences, 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 ultimately 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, information about

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<sup>1</sup>This type of therapy is not aimed at replacing traditional guided therapy. Ideally it is used as supplement, and may provide relief in situations where traditional therapy is not immediately available

genre, style or instrumentation. Control can also include fine-grained musical parameters such as a melody, chord progression or musical structure. Generative models can often be controlled with human-composed music, where the provided music is continued, interpolated between or inpainted (generating accompaniments, melodies, or additional musical lines). In LastMinuteGigChalkiadakis, 2022 the music periodically provides stimuli, a noticeable change in the music, based on which the user changes their playing, specifically their rhythm. One way this stimulus could be achieved in generated music is by adding control that introduces a shift in rhythmic patterns at semi regular intervals.

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. I.e an auto-regressive transformer models a sequence based on prior parts of the sequence, it natively generates continuations of an input. In deep learning, other musical parameters (i.e chord progression or melody) can be controlled for 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, or even more training material as the baseline model without controls.

A more economical method of adding control to a deep learning generative model is through fine-tuning and post-hoc conditioning. In fine-tuning (sometimes referred to as transfer learning) a pre-trained model is trained on additional data. There are various methods of fine-tuning, involving different configurations of the model, the model parameter and the integration of control input, but typically fine-tuning uses considerably fewer resources and data than training a model from scratch. In post-hoc conditioning a generative model is adjusted while it is running to increase the likelihood of the output to fit the desired constraints. The goal of this thesis is to steer a pretrained generative model to generate music fit to an MACT context, without training a large model from scratch, but using efficient fine tuning to introduce new control mechanisms to a pretrained model. For this I will first explore and evaluate different methods of adding control using small generative music model. I will then apply the most successful techniques of adding learned from this first step to a larger generative music model, MusicLang to steer the output towards something usable in the context of MACT.

In a final step we will generate a large amount of music to extend the LastMinuteGig video game for MACT in patients with Parkinson's. LastMinuteGig is a mobile application built with Unity3D. In its current iteration it contains a single button with which a player taps along to the music, controlling a set of guitar chords. When a musical change occurs the player is instructed to change their tapping. It uses a simple music generation process based on recombination,

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which I aim to replace with a set of generated music.

## 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 Control Music Generation.

### 2.1 Why Generate Music? - Motivation

#### 2.1.1 Composition Co-Pilots

The earliest music generators (including the 18th-century musical dice gamesNierhaus, 2009) were justified as methods to inspire composers and music makers, including enabling novice composers to write music. Composer David CopeCope, 1989 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” n.d. Many current and past efforts highlight music generation as a process that assists composers. In DeepBachHadjeres et al., 2017, 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<sup>1</sup> to support musical inpainting in Ableton Live scores. Similarly, with Composer’s AssistantMalandro, 2023, 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 ContinuatorPachet, 2003 and Ben-Tal’s musical dialog systemKite-Powell, 2023.

#### 2.1.2 Music in Games

Beyond co-creating music, AI-generated music serves functional purposes, such as background music in videos and therapy-assisting games. In gaming, AI-generated or AI-assisted music is

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<sup>1</sup><https://github.com/SonyCSLParis/music-inpainting-ts>

particularly relevant 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 timePlut and Pasquier, 2020; Worrall and Collins, 2024. 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 Rogers and Weber, 2019 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 music generation remains underutilized. Composing and adapting music for every possible scenario would be tedious. AI-assisted music composition could 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 appropriatePlut and Pasquier, 2020. Furthermore, AI music generators currently lack proper integration into video game environments and enginesWorrall and Collins, 2024.

### **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 therapyDjaouti et al., 2011. In music therapy, music can be used for emotion regulation, motivation, adherence, motor coordination, rhythmic entrainment, and facilitating social interactionsAgres et al., 2021. Musical attention control training has been shown to help individuals with Parkinson’sPark and Kim, 2021, ADHDMMartin-Moratinos et al., 2023, autismPasiali et al., 2014, and psychosisvan Alphen et al., 2019 improve their mental capabilities for selective and switching attention. Serious games have the potential to supplement music therapy. “Last Minute Gig”Chalkiadakis, 2022 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. SchletteSchlette, 2022 attempted 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 oversaturation of cultural spaces with low-quality generated content, and the environmental impact of large generative models, which require substantial energy, water, and rare materials to operate.

### **2.2.2 Data Leakage and Copyright**

Generative AI companies are achieving record-breaking valuations and this includes music generators with Suno at a valuation of about 500 million dollars after a 125 million dollar fund-raiser leading the pack. Stassen, 2024 Tencer, 2024. However, AI companies are facing backlash from artists and record labels with an organization of record labels including the “big three” Sony, Warner Music, and UMG suing Suno and Udio for \$150.000 dollars per infringed work Kaba et al., 2024. 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 Duan et al., 2024. While leakage may raise privacy concerns in other generative models such as speech and image-generators Carlini et al., 2023 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 influenced Newton-Rex, 2024 to leak training data. This ability to create disconcertingly close reproduction of copyrighted work is also cited in the 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 Reed, 2024, 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.”Copyright Law of the United States Title 17, Chapter 1, Section 107”, n.d. Fair use is often granted to derivative works such as parodies and covers and works used in educational settings. AI’s learning of structures has also been likened to the human learning process, humans learn based on copyrighted music they listen to, without giving credit or compensation to their influences. Newton-Rex Newton-Rex, 2024 rejects this comparison. In learning music, humans contribute to the musical ecosystem, they take lessons, go to performances, or at the very least generate 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 are following director Ram Gopal Varma’s announcement to only use AI-generated music in his future films Singh, 2024, AI-generated music is becoming increasingly difficult to differentiate from human production and already receiving considerable amounts of streams and it is not unlikely that music in film, video and game projects may be replaced or at least supplemented with AI-generated music. The online music market is saturated, with more than 100,000 songs uploaded to music streaming giant Spotify every day Stassen, 2023. Generative AI may just further exacerbate this problem, resulting in a race to the bottom for creatives and musicians.

#### **2.2.5 Environmental Impact**

Digital infrastructure, traditional data centers, crypto-currency mining, and AI-centered data infrastructure account for about 2% of the world’s energy consumption Marechal, 2024. The performance of current large language models often scales with simultaneous increases in model size, training data, and computation time.Kaplan et al., 2020 Each of these three factors requires considerable resources. Music generation is no exception. In a recent ISMIR publication Holzapfel et al., 2024 the authors make estimates on energy consumption of different projects related to music generation and computation-intensive MIR, finding an average energy consumption of 224.8kWh 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 estimated energy use. 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 important to keep in mind.

### 2.2.6 How I plan to address these concerns

During this thesis process, I'm planning to address the outlined ethical concerns in the following manner. First, I will only train, and use open-source models trained on licensed data providing attributions where possible. I will also make my trained models publicly available with substantial documentation to contribute to the open-source ecosystem, research, and music. Second I am explicitly designing the generative process to be cooperative, this is facilitated on the one hand through the introduction of new control modalities, and on the other the choice of symbolic music over audio, which eases editing and integration into composition software. Finally, I am not attempting to train custom large foundation models, rather I'm 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 France-Presse, 2016 and providing musical material themselves, such as in the 1957 Illiac suite Hiller and Isaacson, 1959. The following 50 years are characterized by disparate, academic experiments in music generation, mostly in the symbolic music domain. They utilize a variety of contemporary AI technologies, from expert systems and ontologies Hiller and Isaacson, 1959 Ebcioglu, 1994 to evolutionary algorithms Polito et al., 1997 to feed-forward Todd, 1989, recursive Mozer, 1994, and convolutional neural networks Chakraborti et al., 2020. Some composers in the classical tradition, such as Iannis Xenakis Xenakis, 1992 and David Cope Cope, 1989 use computer algorithms in their creative work. In the 2010s a small ecosystem of commercial generative music startups such as Jukedeck, PopGun, and Ampermusic Featherstone, 2017 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 Yang et al., 2017, DeepBach Hadjeres et al., 2017 and FolkRNN Sturm and Ben-Tal, 2016. With the development of the transformer architecture in 2017 Vaswani et al., 2017, large technology companies start experimenting with music generators including OpenAI's Jukebox Dhariwal et al., 2020 and Musenet Christine, 2019, Meta's MusicGen Copet et al., 2023 and Google's MusicLM Agostinelli et al., 2023 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 Stassen, 2024, while gener-

ated music is being widely streamed and actively used in TV and video productions.

## 2.4 Non-neural music generation

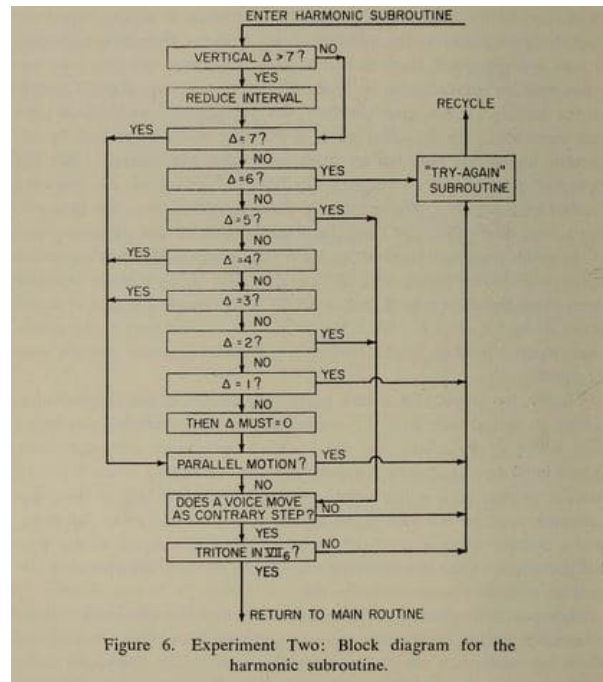
### 2.4.1 Why look beyond deep learning

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 (more in section ??), it is worthwhile considering alternative approaches to music generation. A recent study Yin et al., 2023 performs a comprehensive listening survey comparing neural net and non-neural net systems. The top-performing systems a Markov Model - MAIA Markov Collins and Laney, 2017 and a deep learning system - MusicTransformer C.-Z. A. Huang et al., 2018 perform similarly well in the listening study. The choice of one of the earliest transformer-based music from 2018 C.-Z. A. Huang et al., 2018 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 musical writing from ancient Mesopotamian tuning charts Mirelman, 2013 to Fux's *Gradus ad Parnassum* Fux, 1725 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 Fux, 1725, 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 Isaacson's approach is relatively simple, using only a handful of conditions (see figure ??).

Rule-based generation can be highly complex, such as CHORAL Ebcioğlu, 1994 (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. 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" Pinkerton, 1956. Markov chains can be nested or constrained for more complex interactions Collins and Laney, 2017. In Hiller and Isaacson's Hiller and Isaacson, 1959 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 Pachet, 2003, but training over a whole corpus is also viable. Other systems configure Markov chains to take additional inputs into account, such as Allan, Allan, 2002 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 Altay and Alatas, 2018. In Morpheus, Herremans and Chew, 2019 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 Politio et al., 1997 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. Todd, 1989 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. Future work based on RNNs uses the latter principle, such as CONCERT, Mozer, 1994 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 Hild et al., 1991, 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 Sturm and Ben-Tal, 2016, a melody generator trained on Irish folk songs, use long short-term memory (LSTMs) or gated recurrent units (GRUs). Generative Adversarial Networks (GANs) and Vari-

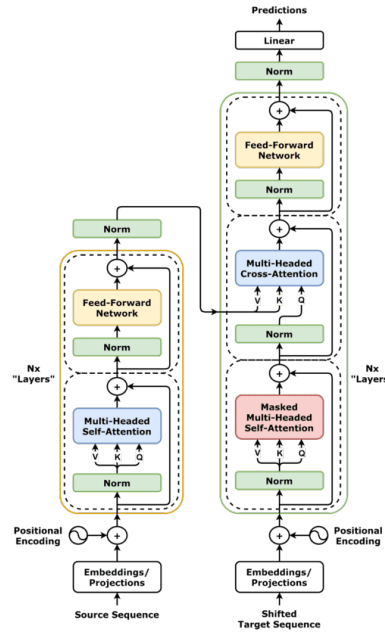
ational Autoencoders (VAEs) remain popular architectures for music generation. Civit et al., 2022

## 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

Autoregressive music generation draws from successful natural language modeling tasks powered by the transformer model. Transformers were originally developed for the task of language translation. Vaswani et al., 2017 They keep the self-attention mechanism already deployed in LSTMs for seq2seq tasks Sutskever et al., 2014 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 ?? . Often, tasks relating to sequence understanding, such as music classification, use an encoder-only architecture. The BERT series of language models Devlin et al., 2019 and music understanding models such as MusicBERT Zeng et al., 2021 are examples. On the other hand, sequence generation tasks often employ a decoder-only architecture, this includes the GPT-series Radford et al., 2019 and many music generators such as MusicGen Copet et al., 2023. The transformer architecture is the baseline for all current large language models. Transformers are used in modalities beyond text, including images, audio, or DNA sequences.



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

<sup>a=</sup> 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 Liu et al., 2023, and StableAudio Evans et al., 2024 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 Min et al., 2023 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.

In this thesis, we will be targeting transformer models. Transformer models are tremendously popular and behind many state-of-the-art results in music generation. There is a tremendous amount of interest in model fine-tuning and control. In addition, many efforts aim to efficiently adjust models to related tasks without going through the relatively costly training procedure of large models. There is a large selection of open-source models that generate music and excellent infrastructure to support the training and evaluation of those models.

## 2.6 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 out-



put, and what features can be controlled. Second, tokenization, the method in which symbolic or audio data are chunked and ingested into the model is an important aspect, with tradeoffs to consider for different generative tasks and goals.

### **2.6.1 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 consist 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 restricted to pitch, duration, and instrumentation, which sometimes is extended to include formatting information such as bar lines, etc. 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 remains an unsolved issue. Ji et al., 2024 Chen et al., 2024 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 take into account is size. Raw audio is significantly larger than a corresponding digital score. In addition, rendered audio is difficult to edit once generated.

### **2.6.2 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 Dhariwal et al., 2020 uses a variational autoencoder Kingma and Welling, 2014 with a discretizing bottleneck (VQ-VAE) to create tokens from audio. Musicgen Copet et al., 2023 tokenizes audio using the previously developed Encodec model for audio compression which similarly to VQ-VAE, learns a highly condensed discrete representation of audio Défossez et al., 2023. These condensed encodings are crucial for generative modeling on audio.

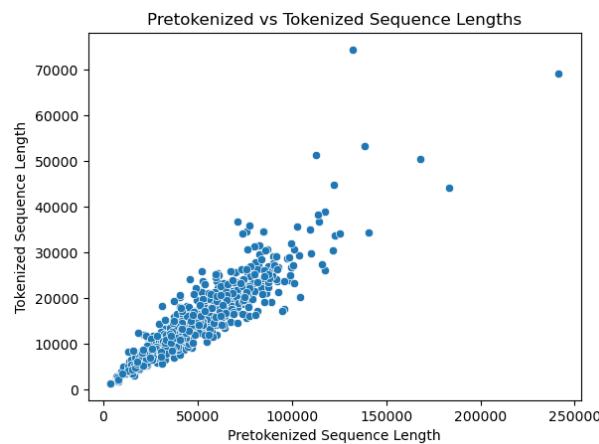
### **2.6.3 Symbolic Tokenisation**

Due to its discrete representation, symbolic music is typically not condensed further (with some notable exceptions, such as condensed piano roll representation for symbolic music diffusion Min et al., 2023 Zhu et al., 2024). However, the choice of tokenization influences the model's per-

formance on different music generation tasks. Fradet et al., 2021. Common ways of tokenizing symbolic music align closely with the musical instrument digital interface (MIDI) standard, with individual tokens encoding different midi-events such as note-on, note-off, and velocity. The REMI+ Y.-S. Huang and Yang, 2020 tokenization expands on MIDI-based tokenization with tokens for bar and position, designed to help capture recurring musical patterns. The PerTok tokenizer designed by Lemonaid<sup>2</sup> 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 can become very long, which adversely affects the model Ji et al., 2024. Ongoing attempts are made to condense token sequences, such as compound words or nested tokens. Ryu et al., 2024. Dong et al. Dong et al., 2023 combine six different MIDI-like events (type, beat, position, pitch, duration, instrument) into single tokens. Hsiao et al. **compound\_word\_Hsiao\_Liu\_Yeh\_Yang\_2021** 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) Sennrich et al., 2016. BPE is used widely in language modeling, including the GPT series of models Radford et al., 2019 and has been successfully applied to symbolic music generation. Fradet\_Gutowski\_Chel\_Briot\_2023 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 ??, 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 individual vs bpe-tokenization sequence lengths

<sup>2</sup><https://www.lemonaide.ai/>

See table ?? in the appendix for a more elaborate display of representations used in symbolic music generators

Herremans and Chew, 2019

## 2.7 Control

Control is an essential aspect of any generative model. Without control, even the best generative models producing beautiful music would be of very limited real-world use. Control allows generative AI tools to become proper collaborative systems, and generate for a wide array of scenarios. In music generation control covers essentially all musical parameters. Parameters vary by representation, symbolic music for instance leaves very little room for any type of timbre control (aside from instrument selection). “Raw” audio models such as Stable Audio (Evans et al., 2024) can for instance 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. For musical parameters represented in symbolic music, there are different approaches to classifying them. We can differentiate between global and local features Van Kranenburg et al., 2013 or deep vs surface-level features Blacking, 1971.

**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 McKay, 2004 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 Van Kranenburg et al., 2013. **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 Van Kranenburg et al., 2013.

Also relevant in the music generation context are abstract vs concrete features. Music generation can take abstract concepts such as genre Rouard et al., 2024, Lu et al., 2023 or emotion Tan and Herremans, 2020 Lu et al., 2023 into account, which in turn effects more complex dynamics of concrete features. To illustrate: In Music FaderNets Tan and Herremans, 2020 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 labeled musical data with the abstract feature is less available, it can also aid in creating more accessible and interpretable generative

models.

In the context of this thesis we differentiate between global features, and fine-grained or time-varying features Rütte et al., 2023. What is time-varying or global is highly context dependent, a piece may have one time-signature and tempo as is assumed in Lu et al., 2023 or it may vary over time as is suggested in Rütte et al., 2023 or Y.-S. Huang and Yang, 2020. Other time varying controls could be chords Rütte et al., 2023Wu et al., 2023Lan et al., 2024Min et al., 2023, melody Copet et al., 2023Min et al., 2023 or texture Min et al., 2023. For the target application in an MACT - game, time-varying controls are necessary to provide a change in music that triggers a change in the patients improvisation. For a more complete list of the types of controls in many of the common symbolic music generators refer to table ?? in the appendix.

### 2.7.1 Rhythmic control

The types of control exercised over rhythmic components varies by representation as discussed in ?. In CocoMulla Lin et al., 2024 generated audio is conditioned with drum tracks and a piano-roll. Similarly in JASCOTal et al., 2024 drums are used for conditioning. In MusicConGen.Lan et al., 2024control for rhythm is added through tracking beats and downbeat. MusicControlNetWu et al., 2023 adds beat and downbeat conditioning to an audio diffusion model. For symbolic systems control of tempo and meter is relatively common Rütte et al., 2023, Y.-S. Huang and Yang, 2020, Lu et al., 2023. More fine grained control over rhythm is sometimes deployed through note-density (both vertical and horizontal)Rütte et al., 2023,Y. Huang et al., 2024. Another option is control over texture, which merges harmonic and rhythmic elements. In PolyffusionMin et al., 2023, texture is encoded by a pretrained variational auto-encoderWang, Wang, et al., 2020. Another approach Zhu et al., 2024 involves passing the piano-roll as factor to guide the diffusion process.

Specifically this thesis investigates adding a certain type of control of rhythm. While generative models feature control of drums Lan et al., 2024, tempo, note-density or meter Rütte et al., 2023, Y.-S. Huang and Yang, 2020, control using inner metric weight, or any complex symbolic characterization of rhythm is novel. However given the success of this characterisation in classification and music-identification tasks it is a promising control feature. The closest approximation is that of texture Min et al., 2023 which has been deployed to some success in diffusion model using VAE disentanglement of harmony and melody.

### 2.7.2 Target Features

In order to extend LastMinuteGig with generated music containing appropriate cues we are targeting control of rhythmic patterns. The most simple way of targeting rhythmic patterns is through note density, implemented as a bar-level instruction of how many notes the following

bar should contain. A second simple target feature is note variability (unique notes per bar over number of notes per bar). Both note-density and note-variability are simple time-varying features that are easily extracted, tokenized and introduced to the algorithm.

A potential approach, novel to music generation, would be control mechanisms using either spectral weight or inner metric weight. Here the weight profile is passed as a control mechanism either globally or on a per bar or per section level. *Comment: Introducing the control at a per bar level would be a bit odd since the idea of metric weight is about extracting weights not reflected in the symbolic grid, but it is a sensible way to introduce it to the model in bite-sized chunks able to reflect local change.* Inner metric and spectral weight weight has been successfully applied to dance music classification Chew et al., 2005, meter detection Haas and Volk, 2016 and music retrieval Volk et al., 2009. This suggests that it is a powerful feature for explaining various rhythmic aspects, which may make it a good guiding mechanism.

## 2.8 Implementation of control

Adding control to generative models can be split into three approaches. 1: Choice of architecture and training data, 2: fine-tuning approaches, and 3: external conditioning or guidance.

### 2.8.1 Control through architecture

The choice of architecture lends itself to different types of control. Transformers are next token predictors, that predict based on the prior sequence. The default training paradigm allows for conditioning with a user defined musical (or audio) sequence. This is true for both audio based models such as MusicGen Copet et al., 2023, Jukebox Dhariwal et al., 2020 and MusicLM Agostinelli et al., 2023 as well as symbolic music models such as MMT Dong et al., 2023, MusicTransformer C.-Z. A. Huang et al., 2018 and MusicBERT Zeng et al., 2021.

Diffusion models are quite flexible compared to transformers, the same model can be used for inpainting, continuation and depending on the representation melody and accompaniment generation through masking. Min et al., 2023 Rombach et al., 2022

### 2.8.2 Control through training conditioning

Control can be added through training data. MusicGen Copet et al., 2023, a recent text-to-music (audio) transformer is trained on 20000 hours of licensed music from shutterstock and pond5<sup>3</sup> 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

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<sup>3</sup><https://www.shutterstock.com/music> and <https://www.pond5.com/>

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!*<sup>4</sup>

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 such as genre and tempo. Specialized datasets such as MusicCaps Agostinelli et al., 2023, which contains 5500 text music pairs, with 10 seconds of music alongside a free text description and a list of aspect tags created by human experts still suffer substantially from subjectivity Lee et al., 2023.

For this reason, the creators of MusicGen Copet et al., 2023 add melody conditioning alongside text conditioning and train their model jointly with the chromagram of the melody alongside the text.

In MusicGenStyle Rouard et al., 2024 perform 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 tokens that are combined with the embeddings of the text-description. Both the style tokens and text tokens are provided as prefix to the model. The conditioner and the MusicGen transformer are trained jointly on the entire dataset.

The creators of FIGARORütte et al., 2023 enable fine grained control over instrumentation, note density, average pitch and volume on a bar-by-bar basis, in a symbolic music generator through joint conditioning while training.

### 2.8.3 Adding control through fine-tuning

Both the melody conditioning of MusicGen Copet et al., 2023 and the style conditioning of MusicGenStyle Rouard et al., 2024 retrain the entire MusicGen model on the entire dataset which comes at considerable cost. Fine-tuning or transfer learning is another method through which models can be trained but at considerably smaller cost and using less data. This is particularly useful and widely used in the language domain to adjust large language models for niche use-cases, where the available data may simply 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 since the controlling elements, melody and style can be inferred from the training data. However fine-tuning is also helpful for adding new control mechanisms.

MusiConGen Lan et al., 2024 is a fine-tuned variation of MusicGen which adds rhythm and chord control. They propose the jump-finetuning mechanism, where the original model with

<sup>4</sup><https://www.pond5.com/royalty-free-music/item/95908062-inspiring-dramatic-epic-background-cinematic-music>

1.5 Billion parameters and 48 self-attention layers, is split model into blocks consisting of 4 self-attention layers. They refine the first layer of each block, freezing the remaining layers. Additionally, they apply adaptive in-attention to the first 9 blocks, where the output of the transformer 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* Lin et al., 2024 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* Shu et al., 2024 is a fine-tuned version of *MuseCoco* Lu et al., 2023 which extends the global controls with fine-grained 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 a section of music corresponds with the control tokens, the body of the model is trained together with a classification head (which is removed after auxiliary task training). In the third step they introduce counterfactual loss where the difference in negative log likelihood conditioned on the original and changed attribute is maximized, which reinforces the models attention to the control. They find that the combination of the three strategies, pre-adaptation on a separate task followed with counterfactual-loss and prompt augmentation yields the strongest model.

#### **2.8.4 Adding control through guidance**

There are also other methods that do not involve any finetuning or retraining of the original model. Adding control through rule labels, or control tokens as in *Rütte et al., 2023* Lan et al., 2024 does require some amount retraining, which is not always feasible, and adding many different types of control may deteriorate the model. In these cases, guidance can be used to steer the model towards a certain output. In *SMITIN* Koo et al., 2024 the authors use inference time intervention to guide a model towards a certain output with respect to certain goals. The goals explored are the presence of certain instruments (piano/drums/bass/guitar) in the mix and the quality/realism of the music. The authors train linear probes that learn to associate a state of the attention heads with the stated goal. Then the attention heads are steered in the direction of the probe's output, which increases the probability of the desired quality being present in the generated music.

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 certain goal. In Y. Huang et al., 2024, each sampling step is repeated several times, and each time the sample that follows a set of rules most closely is chosen. ControlNet Zhang et al., 2023 adds spacial control to image generators allowing the guidance of image generation using sketches, poses, edges and depth maps without retraining. MusicControlNet Agres et al., 2021 adapts this approach to music generation adding control for time varying factors, melody, dynamics and rhythm.

## 2.9 Evaluation

How to evaluate generated music is still an open research question. There are no standardized methods according to which evaluations happen Yin et al., 2023. In the context of music generation there are several proposed frameworks to evaluate music. Typically we differentiate between subjective and objective evaluations.

For subjective approaches the methods vary widely Xiong et al., 2023. There are simple Turing-type evaluations that test how distinguishable generated and human written music are. Then there are subjective query metrics, where typically likert ratings of different parameters are collected. Min et al., 2023 There are tournament style surveys, where the number of winning pieces are tallied for each approach. C.-Z. A. Huang et al., 2018 Rütte et al., 2023 Finally there are expert evaluations (which can also include likert ratings) but also analysis of the produced score and musical structure. Sturm and Ben-Tal, 2016 These evaluations are often paired with statistical hypothesis testing. Rütte et al., 2023

Automatic evaluation of generated music include model specific metrics and different musical metrics Xiong et al., 2023. Model specific metrics are generic evaluations of a models 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 C.-Z. A. Huang et al., 2018, Root Mean Square Error Rütte et al., 2023 or Perplexity Rütte et al., 2023. Musical metrics typically involve comparing a set of generated music to a set of real music, there are plenty of musical similarity measure techniques Gurjar and Moon, 2018 for a large variety of different use-cases i.e 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 metrics i.e count of intervals or unique pitch-classes. However to obtain the 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. Music-



Gen Copet et al., 2023 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 Kilgour et al., 2019. Finally they use the CLAP-score which compares the corresponding text description to the latent representation of the generated audio, with text-description of the generated audio with the reference audio. Elizalde et al., 2023

For this thesis we are interested in two factors, first the plausibility of the generated music, and second the success of the control. How the success of control is evaluated depends on what is controlled for, Examples of controlled parameters and how they are evaluated are as follows:

**Note Density.** (how many notes per bar). Root mean square error (RME) between generated vs target notes per bar. This is the approach to compare note density used in Rütte et al., 2023

**Note Variability** (number of unique pitch classes, normalized by number onsets) - RME between generated and target.

**Rhythmic patterns.** Partial Similarity Volk et al., 2009 between target and generated music:

Evaluating the plausibility of generated music is more complex, and there is no one method that has been proven superior. Possibly the plausibility of the music will be evaluated with a (small) subjective study. In this scenario we would follow Dong et al., 2023, Yu et al., 2022 and Chen et al., 2024 and collect likert ratings on questions targeting Coherence Richness Arrangement and Consistency . These are would be paired with questions on musical background and preferences of the participant. For objective rating of the plausibility of the music we will follow the approach by Min et al., 2023 where the KL-divergence between the corpus of generated and a corpus of original music is calculated, most likely KL divergence over a set of extracted features, such as a pitch classes and chords. For a more complete list of different evaluation methods used on symbolic music generators, refer to the notes in the abstract ??.

### 3. Research Questions

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

The focus of the thesis will be developing a model that generates a complete musical piece with time-varying controls for inner metric weight. The output of the model will be investigated for successful integration of control, for player enjoyment and for interactive potential in the context of MACT.

1. Research Question 1: Can we effectively control for inner metric weight in generated music?.
2. Research Question 2: Do shifts in metric weight provide a recognizable in-game cue?
3. Research Question 3: Does the generated music improve player enjoyment and engagement over ChalkiadakisChalkiadakis, 2022 rule based system.

## 4. Methodology

To answer **RQ1** we develop, train and evaluate a model conditioned with inner metric weight. **RQ2** and **RQ3** are both answered using a user study that collects metrics on player interactions with the music alongside survey responses.

### 4.1 The Model

Sections ?? and ?? 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 model sequences whether it be language or music as well as its potential to incorporate additional controls. We will be using a symbolic representation of music (as discussed in section ??) due to its lightweight datasets and the ability to make changes 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 be using a representation similar to REMI+ (see section ??), a representation that extends the standard MIDI-events with tokens indicating form, such as meter, bar-lines and note-duration. This representation will be compounded using byte pair encoding (see section ??) to decrease the sequence length and improve the capability and efficiency of the model. For adding control (section ??) we will focus on methods that don't require full training, specifically parameter efficient fine tuning and guidance. This is more cost-effective and environmentally friendly. We will use the Lakh Midi Dataset Raffel, 2016, a widely used open source and licensed dataset for symbolic music generation. This will help us avoid ethical pitfalls around privacy and copyright. (section ??). Finally, we are not attempting to add control by training custom large foundation models, rather we are using parameter efficient fine tuning or guidance (section ??) to add control using no or only a fraction of the model parameters, with substantially less need for data, computation, and energy. All relevant code for including code for training, configuration and data-preparation will be made available online alongside the model weights. Finally I 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 widely available in well documented and continuously maintained ecosystem, with integrations into mainstream music production and composition software.

## 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 systemetized 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 the best course of action. We use BassCraft a smaller model, and start by controlling for note-density (the number of notes in a bar), a feature that is more easily calculated, tokenized and verified as opposed to inner metric weight.

#### 4.2.1.1 BassCraft - a tiny transformer model

To avoid wasting valuable compute resources and energy we perform the preliminary experiments on a smaller model: Basscraft. BassCraft is a small transformer model based on GPT2 Radford et al., 2019. It has an embedding size of 256, 4 attention heads, 4 hidden transformer layers, and a total of 7 million trainable parameters. For contrast the target LLAMA 2 based model MusicLang has over 100 million trainable parameters. Basscraft is trained to generate a bassline to a provided piece of music using the lakh-midi dataset Raffel, 2016. For training, songs with bass-lines are selected (based on the presence of particular MIDI-instrument channels). The tracks are partitioned into snippets between 1 and 16 bars long. The bass-lines are separated from the remaining track and matched as potential output.

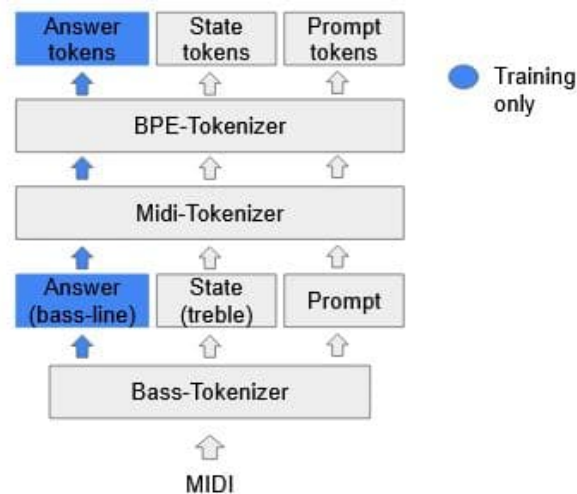
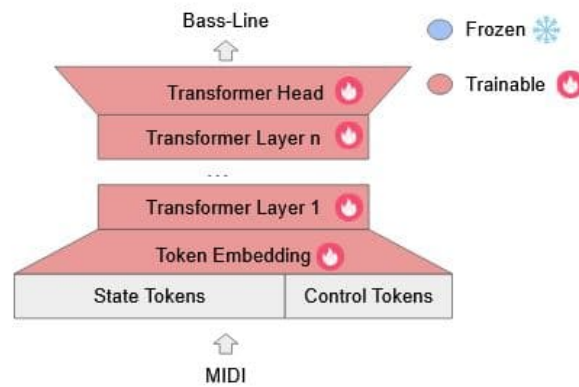


Figure 4.1: Preprocessing/tokenization of the original basscraft model

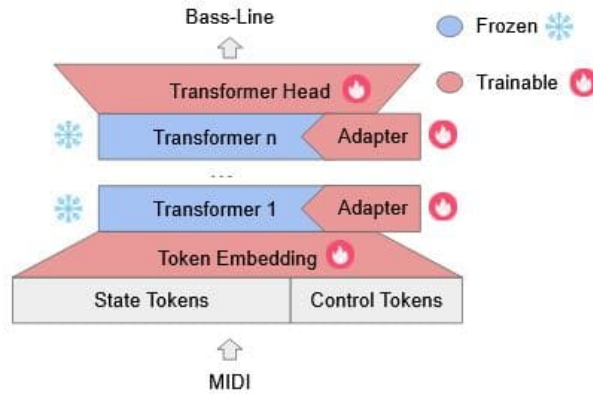
#### 4.2.1.2 Fine-Tuning 1 - Vocabulary Extension

Vocabulary expansion is the process to add new vocabulary to a transformer model. MusicLang achieves it's extraordinary controllability similarly to FIGARO Rütte et al., 2023 using

control tokens, that summarize features of the music that go beyond simply representing MIDI-events. In vocabulary extension it is critical to ensure that additional tokens do not overwrite or otherwise collide with the existing training, otherwise the benefit of using a priorly trained model is eliminated. Since we are using a BPE tokenizer, is difficult to simply add new tokens here, as it would require retraining the BPE tokenizer, which will transform the embedding layer making the entire model unusable. Instead we investigate whether there are unused tokens, and reassign them to our new control tokens. These new tokens will not be included in any of the compound tokens generated by the BPE process, which does negativley effect the sequence length.



**Figure 4.2:** Vocabulary transfer with full fine tuning

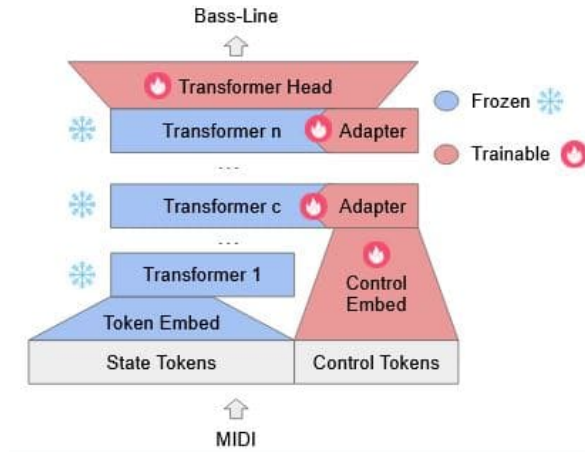


**Figure 4.3:** Vocabulary transfer with parameter efficient fine tuning

#### 4.2.1.3 Fine-Tuning 2 - Integrating of control tokens

This approach is slightly different from the vocabulary extension, because it processes the additional control tokens as a parallell stream. This is similar to the the approach used in Coco-Mulla Lin et al., 2024. The parallell stream of control tokens is inserted into the model after c layers (with bypasses that insert the embedding into every following layer), after passing through a custom learned embedding. The benefit of this method is that it doesn't require editng the

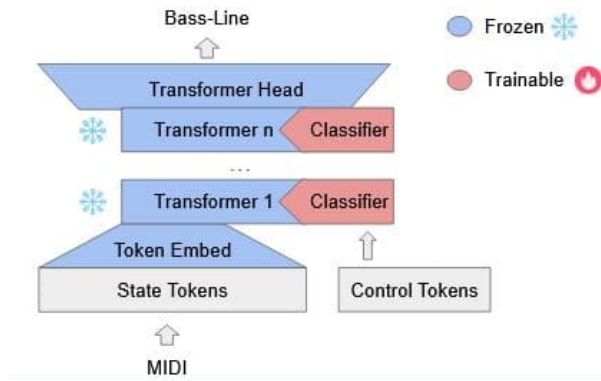
model's vocabulary.



**Figure 4.4:** Integration of control tokens with parameter efficient fine tuning

#### 4.2.1.4 Post-Hoc Guidance and other improvements

This is the approach used by SMITINKoo et al., 2024. This type of sampling based guidance has been very successful in diffusion models, however in transformers it produces mixed results [language\\_guide\\_rutte\\_2024](#). One potential problem: This may be very difficult to implement. Both SMITIN and Rüttel [language\\_guide\\_rutte\\_2024](#) only use one dimensional variables (probability of a concept being present or not).



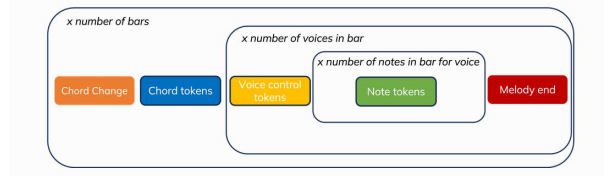
**Figure 4.5:** Integration of control using inference time interference

If these experiments are not successful, we can follow the approach of Shu et al., 2024 and try additional training using auxiliary tasks and using a modified (counterfactual) loss function.

## 4.2.2 MusicLang - The foundation Model

After concluding the preliminary experiments and identifying a promising set of methods. We will proceed with the larger MusicGen model. MusicLang's core model is a transformer

based on LLAMA 2 trained on the Lakh Midi DatasetRaffel, 2016. It can generate relatively long multi-track instrumental pieces, (a couple of minutes) with control for chord progression, instrumentation and range. Additionally it can generate interpolations and continuations of a user provided piece. It is trained on an extended vocabulary of tokens similar to REMI<sup>1</sup> with additional tokens detailing harmonic structure and voice characteristics i.e instrumentation or range (see figure ??). This base vocabulary is additionally extended using the BPE tokenizer. The goal of this section is to extend MusicLang with control for inner metric weight.



**Figure 4.6:** MusicLang tokenisation on a high level

### 4.3 User Study

#### RQ2 and RQ3

The first step in this experiment is extracting and tokenizing either spectral or inner metric weight which is then tokenized and passed to the MusicLang Llama 2 model. They will be integrated with the most successful method determined above.

This will be followed by a user study on healthy participants following the original protocolChalkiadakis, 2022

<sup>1</sup><https://musiclang.github.io/tokenizer/>

4.4 Thesis Timeline

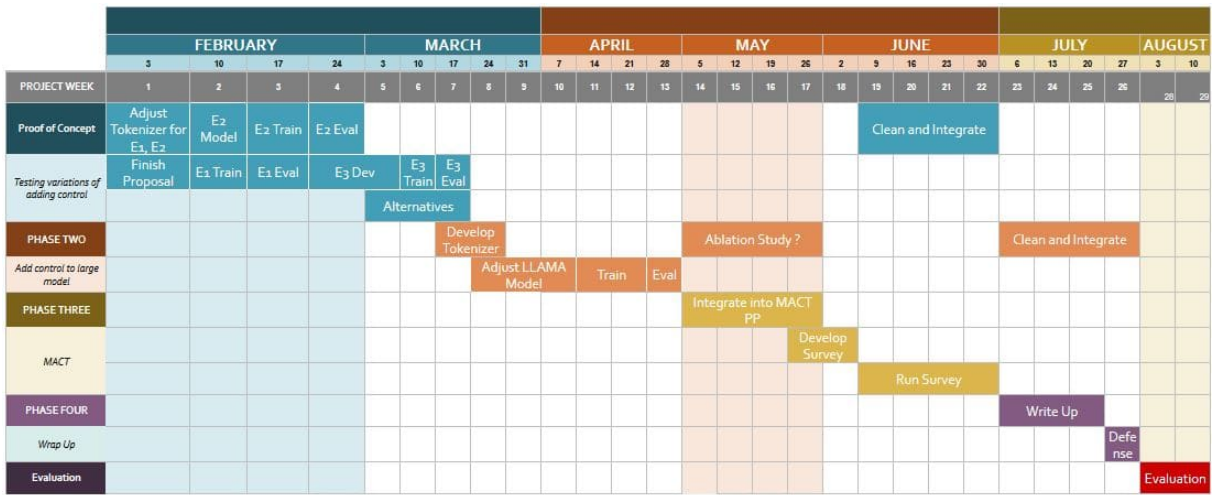


Figure 4.7: Thesis project plan



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## 5. Appendix

### 5.1 Comparing Tokenization lengths

Pretokenized Sequence Lengths - Mean: 47976.146146146144, Median: 43692.0, Std Dev: 23159.918513030065  
Tokenized Sequence Lengths - Mean: 14519.587587587588, Median: 13159.0, Std Dev: 7197.064427699848

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.

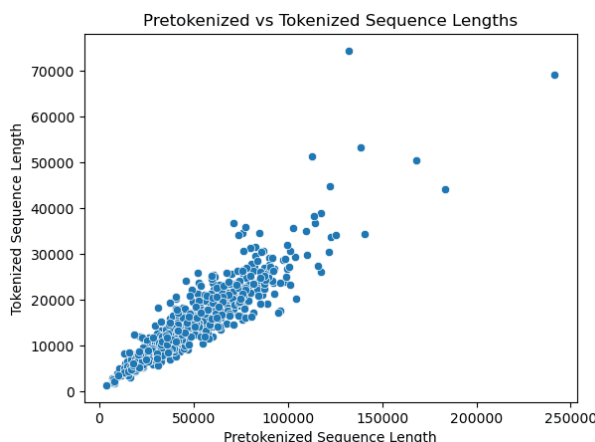


Figure 5.1: Scatterplot of Pre-tokenization vs bpe-tokenization sequence lengths

### 5.2 Integration into LastMinuteGig 2 months

This project is motivated by extending the music engine of LastMinuteGig. Chalkiadakis, 2022. The application currently employs a very simple algorithm. I will outline it below.

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

This music engine will be changed in the following way. Most of the generative process will be done asynchronously.

- 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.

Name	Architecture	Control	FG	MI	Dataset
DeepBach (2017) Hadjeres et al., 2017	RNN	Inpainting	Yes	Yes	"Canonical"
FolkRNN (2015) Sturm and Ben-Tal, 2016	RNN	meter, mode	No	No	Keith, n.d.
MT (2018) C.-Z. A. Huang et al., 2018	Transformer	-	No	No	Hawthorn
MidiNet (2019) Yang et al., 2017	GAN	chords, melody	Yes	Yes	"Hook The
Polyfussion 2023 Min et al., 2023	Diffusion	inpainting), texture	Yes	No	Wang, Che
FIGARO 2023 Rütte et al., 2023	Transformer	chords, instr, meter, nd	Yes	Yes	Raffel, 201
MMT 2023 Dong et al., 2023	Transformer	instrumentation	No	Yes	Raffel, 201
OMT 2020 Y.-S. Huang and Yang, 2020	Transformer	chords, tempo	Yes	No	C
MuseNet 2019 Christine, 2019	Transformer	instr, genre	Yes	Yes	Hawthorn
MMM 2020 Ens and Pasquier, 2020	Transformer	inpainting, instr, nd	Yes	Yes	Raffel, 201
Sympack 2024 Chen et al., 2024	Transformer	chords, structure, notes	Yes	Yes	Raffel, 201
MuseCoco 2023 Lu et al., 2023	Transformer	various	No	No	C
MBC 2024 Shu et al., 2024	Transformer	chords	Yes	No	Wang, Che
Museformer 2022 Yu et al., 2022	Transformer	-	No	Yes	Raffel, 201
NTT Ryu et al., 2024	Transformer	-	No	Yes	Raffel, 201
FTG Zhu et al., 2024	Diffusion	texture, rhythm, chords	Yes	No	Wang, Che
Fader Nets	VAE	rhythm, arousal	No	No	Hawthorn
NDRD Y. Huang et al., 2024	Diffusion	chord, pitch, nd	Yes	No	Hawthorn

**Table 5.1:** Overview of music generation models, their architectures, and control mechanisms. Empty columns indicate missing information on fine-grained control, multitrack capabilities, dataset, and evaluation methods.

### 5.3 Notes Comparing Symbolic Music Generators and their evaluation methods

- DeepBach Hadjeres et al., 2017 - RNN - inpainting. Evaluation Turing
- FolkRNN Sturm and Ben-Tal, 2016 - RNN - control for meter and mode - Expert Evaluation + Performance Practice
- MusicTransformer C.-Z. A. Huang et al., 2018 - Transformer - Evaluation: Subjective - Tournament Style between different generated and natural music. Objective: Validation NLL
- MidiNetYang et al., 2017 - GAN - Control for Chords/Priming melody. Human (how pleasing, how real, and how interesting)
- Polyfussion Min et al., 2023 - Diffusion Model - supports inpainting, interpolation, melody/accompaniment generation, control for chord progression, texture. Subjective Evaluation Questionnaire for naturalness, creativity, musicality. Objective Control success.
- FIGARO Rütte et al., 2023 - 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) Dong et al., 2023 - 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 - Y.-S. Huang and Yang, 2020 - Transformer - continuation, control local control over chord and tempo
- MuseNet Christine, 2019 - Transformer -,Instrument control, style control. No evaluation, only showcase.
- MMM Ens and Pasquier, 2020 - Transformer model - inpainting, instrument control, note-density. Introduce novel representation No Rigorous Evaluation
- SymPAC Chen et al., 2024 - 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 Lu et al., 2023 - 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), Overall Impression. Comparison with LLM generated music (with no special training for music generation)
- MBD Shu et al., 2024 Extension of MuseCoco for time varying chord controls. Counterfactual Loss and Auxiliary task training improve controllability.
- Museformer Yu et al., 2022 - 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 Ryu et al., 2024 - 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, Consis-

tency, 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 Tan and Herremans, 2020 - 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.