Emotion-Conditioned Polyphonic Music Generation Using Transformer-Based Deep Learning

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***Abstract*—This paper presents a novel approach to automatic music generation conditioned on emotional states using a Transformer-based deep learning architecture. We propose a system that generates polyphonic piano music corresponding to four distinct emotional quadrants: Joy, Tension, Sadness, and Calm, based on the arousal-valence emotional model. Our method employs a decoder-only Transformer architecture trained on the EMOPIA dataset, utilizing an event-based MIDI tokenization scheme that captures pitch, duration, and temporal information. The model learns to generate musically coherent sequences by conditioning on emotion tokens prepended to the input sequence. We implement nucleus sampling for generation to balance creativity and coherence. Experimental results demonstrate that our approach can generate emotionally consistent musical compositions with polyphonic structure. The system achieves convergence during training and produces MIDI outputs that can be rendered to audio format. This work contributes to the field of affective computing and computational creativity by providing an end-to-end framework for emotion-aware music generation.**

***Index Terms*—Music generation, emotional computing, Transformer architecture, deep learning, MIDI processing, affective computing, conditional generation**

I. Introduction

Music has long been recognized as a powerful medium for emotional expression and communication. The ability to generate music that conveys specific emotions has significant applications in entertainment, therapy, personalized content creation, and human-computer interaction. While traditional algorithmic composition relies on rule-based systems and requires extensive musical expertise, recent advances in deep learning have enabled data-driven approaches that can learn complex musical patterns directly from large corpora.

The challenge of emotion-conditioned music generation lies in capturing both the structural complexity of polyphonic music and the subtle relationships between musical features and emotional perception. Previous approaches have employed various architectures including Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and more recently, Transformer models. However, many existing systems focus on either monophonic generation or do not explicitly condition on emotional attributes.

In this work, we address these limitations by proposing a Transformer-based architecture specifically designed for emotion-conditioned polyphonic piano music generation. Our approach is built upon several key contributions:

1) **Event-Based Tokenization Scheme**: We develop a comprehensive tokenization method that represents MIDI data as sequences of discrete events including pitch, duration, and time-shift tokens, enabling the model to capture polyphonic structure.
2) **Emotion-Conditioned Architecture**: We design a conditional generation framework where emotion labels are embedded as special tokens and prepended to musical sequences, allowing the model to learn emotion-specific musical patterns.
3) **Decoder-Only Transformer Design**: We employ a GPT-style autoregressive Transformer architecture with causal masking, optimized for sequential music generation tasks.
4) **Nucleus Sampling Strategy**: We implement top-p sampling during inference to generate diverse yet coherent musical outputs while avoiding the pitfalls of greedy or purely random sampling.

The remainder of this paper is organized as follows: Section II reviews related work in automatic music generation and affective computing. Section III provides a system overview. Section IV details our proposed methodology. Sections V and VI describe the model architecture and data processing pipeline. Section VII presents implementation details and training strategies. Section VIII discusses experimental results and evaluation. Sections IX and X provide discussion and limitations. Finally, Section XI concludes the paper and suggests future research directions.

II. Related Work

A. Deep Learning for Music Generation

The application of deep learning to music generation has evolved significantly over the past decade. Early approaches employed RNNs and LSTMs to model sequential dependencies in musical data. Notably, Eck and Schmidhuber [1] introduced LSTM networks for blues improvisation generation. The development of WaveNet [2] by van den Oord et al. demonstrated the potential of deep generative models for raw audio synthesis, though at significant computational cost.

More recently, Transformer architectures have shown remarkable success in sequence modeling tasks. The Music Transformer [3] introduced by Huang et al. employed relative positional self-attention to capture long-range dependencies in symbolic music. This architecture demonstrated superior performance compared to LSTM-based models on the task of piano performance generation. Similarly, MuseNet [4] by

OpenAI utilized sparse Transformer architectures to generate music across multiple instruments and styles.

B. Emotion-Based Music Generation

The relationship between music and emotion has been extensively studied in music psychology and computational musicology. Russell's circumplex model of affect [5], which organizes emotions along arousal and valence dimensions, has been widely adopted in music emotion recognition and generation research.

Several systems have attempted emotion-conditioned music generation. Kaliakatsos-Papakostas et al. [6] proposed rule-based methods using genetic algorithms to generate melodies with specific emotional characteristics. Ferreira and Whitehead [7] developed an evolutionary approach to generate emotionally expressive music. However, these methods relied heavily on hand-crafted rules and lacked the ability to learn from data.

Deep learning approaches to emotional music generation have emerged more recently. Medeot et al. [8] introduced LSTM-based models conditioned on emotional tags. The EMOPIA dataset [9], introduced by Hung et al., provided a foundation for training emotion-aware music generation systems by annotating 1,087 MIDI tracks according to the four-quadrant arousal-valence model.

C. MIDI Representation and Tokenization

The representation of musical data significantly impacts model performance. Common approaches include piano roll representations, which encode music as binary time-pitch matrices, and event-based representations, which represent music as sequences of discrete events.

The REMI (Revamped MIDI-derived events) representation [10] introduced by Huang and Yang demonstrated advantages of event-based tokenization for capturing rhythmic and polyphonic information. Our approach builds upon this paradigm while simplifying the vocabulary to focus on essential musical elements: pitch, duration, and timing.

D. Positioning of This Work

While existing research has made significant progress in music generation and emotion modeling separately, there remains a gap in developing efficient, Transformer-based systems specifically optimized for emotion-conditioned polyphonic generation with simplified yet expressive tokenization schemes. Our work addresses this gap by combining insights from recent Transformer architectures with emotion conditioning strategies and practical tokenization methods suitable for real-time applications.

III. System Overview

Our emotion-conditioned music generation system consists of four primary components operating in a pipeline architecture: data preprocessing, model training, inference engine, and audio synthesis. Fig. 1 illustrates the overall system architecture.

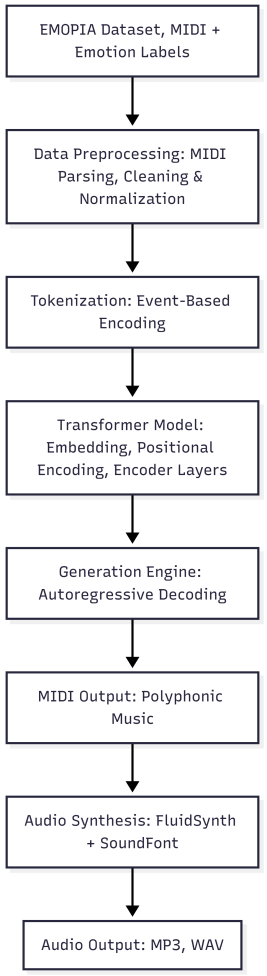

Fig. 1. Overall system architecture showing the pipeline from EMOPIA dataset through preprocessing, tokenization, Transformer model, generation engine to final MIDI and audio output.

A. System Input and Output

Input: The system accepts two types of input:

1) During training: MIDI files paired with emotion labels (Q1, Q2, Q3, Q4) from the EMOPIA dataset
2) During generation: A single emotion label specifying the desired affective state

Output: The system produces:

1) MIDI files containing polyphonic piano music
2) Audio files (MP3 format) rendered using FluidSynth with a SoundFont

B. Emotion Mapping

We employ the four-quadrant arousal-valence model, where emotions are categorized as:

- **Q1 (Joy)**: High Arousal, High Valence
- **Q2 (Tension)**: High Arousal, Low Valence
- **Q3 (Sadness)**: Low Arousal, Low Valence
- **Q4 (Calm)**: Low Arousal, High Valence

This mapping provides a balanced representation of emotional states commonly expressed in Western music and aligns with established music psychology research.

C. Processing Workflow

The complete processing workflow consists of the following stages:

1) **Data Loading**: MIDI files are loaded and paired with emotion labels from metadata
2) **MIDI Parsing**: Musical data is extracted from MIDI format using the miditoolkit library
3) **Tokenization**: Musical events are converted to discrete token sequences
4) **Sequence Preparation**: Tokens are combined with emotion embeddings and special tokens (BOS, EOS)
5) **Training**: The Transformer model learns to predict next tokens given previous context
6) **Generation**: Trained model autoregressively generates token sequences conditioned on emotion
7) **Decoding**: Token sequences are converted back to MIDI format
8) **Audio Rendering**: MIDI files are synthesized to audio using FluidSynth

D. Design Rationale

Several design decisions inform our system architecture:

Single Instrument Focus: We focus exclusively on piano to reduce complexity and ensure data consistency. Piano provides sufficient expressive range for polyphonic music while maintaining timbral uniformity.

Event-Based Representation: Unlike piano roll representations that require dense matrices, our event-based tokenization produces compact sequences suitable for Transformer processing.

Decoder-Only Architecture: We employ a GPT-style decoder-only architecture rather than encoder-decoder, as music generation is inherently an autoregressive task without a separate source sequence.

Modular Pipeline: The separation of tokenization, training, and generation enables independent optimization and debugging of each component.

IV. Proposed Methodology

A. Problem Formulation

We formulate emotion-conditioned music generation as a conditional sequence modeling problem. Given an emotion label $e \in \{Q1, Q2, Q3, Q4\}$, our objective is to generate a sequence of musical tokens $X = \{x_1, x_2, \ldots, x_T\}$ that maximizes the conditional probability:

$$P(X|e) = \prod_{t=1}^{T} P(x_t|x_{<t}, e) \tag{1}$$

where $x_{<t}$ represents all tokens before position t.

B. Token Vocabulary Design

We design a vocabulary comprising the following token types:

1) **Special Tokens** (4 tokens):
   - PAD_TOKEN (0): Padding for variable-length sequences
   - BOS_TOKEN (1): Beginning of sequence marker
   - EOS_TOKEN (2): End of sequence marker
   - UNK_TOKEN (3): Unknown/invalid tokens
2) **Pitch Tokens** (88 tokens):
   - Range: MIDI notes 21-108 (A0 to C8, full piano range)
   - Token range: [4, 91]
   - Encoding: TOKEN_OFFSET_PITCH + (pitch - MIN_PITCH)
3) **Time-Shift Tokens** (100 tokens):
   - Represent temporal displacement between events
   - Token range: [92, 191]
   - Quantized to 16th note resolution
   - Encoding: TOKEN_OFFSET_TIME + quantized_shift
4) **Duration Tokens** (64 tokens):
   - Represent note duration
   - Token range: [192, 255]
   - Quantized to 16th note resolution
   - Encoding: TOKEN_OFFSET_DURATION + quantized_duration
5) **Emotion Tokens** (4 tokens):
   - Represent emotion labels Q1-Q4
   - Token range: [256, 259]
   - Encoding: TOKEN_OFFSET_EMOTION + emotion_id

Total vocabulary size: 260 tokens.

C. MIDI Tokenization Algorithm

The tokenization process converts MIDI files to token sequences through Algorithm 1.

This algorithm produces sequences of the pattern: [TIME_SHIFT?, PITCH, DURATION]* where TIME_SHIFT is optional.

D. Sequence Construction for Training

For training, we construct input-target pairs:

1) Prepend BOS_TOKEN and EMOTION_TOKEN to the token sequence
2) Append EOS_TOKEN at the end
3) Truncate sequences exceeding maximum length (512 tokens)
4) Create training pairs:
   - Input: [BOS, EMOTION, tok_1, …, tok_{n-1}]
   - Target: [EMOTION, tok_1, …, tok_{n-1}, EOS]

This teacher-forcing approach enables efficient parallel training while maintaining autoregressive properties.

Algorithm 1 MIDI Encoding

Require: MIDI file path, ticks_per_beat
Ensure: Token sequence
Load MIDI file and extract all notes from non-drum tracks
Sort notes by (start_time, pitch)
Initialize current_time ← 0, tokens ← []
for each note **do**
  Calculate time_diff ← note.start - current_time
  if time_diff $>$ 0 **then**
    Quantize time_diff to 16th note units
    Append TIME_SHIFT token
    Update current_time
  end if
  Append PITCH token (clamped to piano range)
  Calculate and quantize note duration
  Append DURATION token
end for
return tokens =0

E. Generation Strategy

During inference, we employ nucleus (top-p) sampling to balance diversity and quality as described in Algorithm 2.

Algorithm 2 Nucleus Sampling Generation

Require: emotion, model, temperature, top_p
Ensure: Generated token sequence
Initialize sequence ← [BOS_TOKEN, EMOTION_TOKEN]
while length $<$ max_length AND last_token $\neq$ EOS_TOKEN **do**
  Forward pass: logits ← model(sequence)
  Extract logits for next position
  Apply temperature scaling: logits ← logits / temperature
  Sort logits in descending order
  Compute cumulative probabilities
  Mask tokens where cumulative_prob $>$ top_p
  Sample next_token from filtered distribution
  Append next_token to sequence
end while
return sequence (excluding BOS and EMOTION tokens) =0

The temperature parameter (default: 1.0) controls randomness, while top_p (default: 0.9) limits sampling to the nucleus of the probability distribution, preventing selection of very low-probability tokens.

F. Decoding to MIDI

The detokenization algorithm reverses the encoding process as shown in Algorithm 3.

This process reconstructs polyphonic music from the token sequence while maintaining timing relationships.

Algorithm 3 MIDI Decoding

Require: Token sequence
Ensure: MIDI file
Initialize MIDI object with ticks_per_beat = 480
Create piano instrument (program 0)
Initialize current_time ← 0
for each token in sequence **do**
  if TIME_SHIFT token **then**
    Add (shift_value $\times$ 16th_note_ticks) to current_time
  end if
  if PITCH token **then**
    Extract pitch value
    Look ahead for DURATION token (default if absent)
    Create note at current_time with extracted duration
    Add note to instrument
  end if
end for
Save MIDI file =0

V. Model Architecture

A. Overview

Our model employs a Transformer architecture with causal masking, functionally equivalent to the GPT (Generative Pre-trained Transformer) architecture adapted for music generation. The architecture consists of three primary components: embedding layer, Transformer encoder with causal masking, and output projection head. Fig. 2 illustrates the model architecture.

B. Embedding Layer

The embedding layer maps discrete token indices to continuous vector representations:

$$\mathbf{E} \in \mathbb{R}^{V \times d_{model}} \tag{2}$$

where $V = 260$ is the vocabulary size and $d_{model} = 256$ is the embedding dimension. Each token x_t is mapped to an embedding vector $\mathbf{e}_t = \mathbf{E}[x_t]$.

To stabilize training, embeddings are scaled by $\sqrt{d_{model}}$:

$$\mathbf{e}'_t = \mathbf{e}_t \cdot \sqrt{d_{model}} \tag{3}$$

C. Positional Encoding

Since Transformers lack inherent notion of sequence order, we employ sinusoidal positional encodings:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{4}$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{5}$$

where pos is the position and i is the dimension index. These encodings are added to the scaled embeddings:

$$\mathbf{x}_t = \mathbf{e}'_t + \mathbf{PE}_t \tag{6}$$

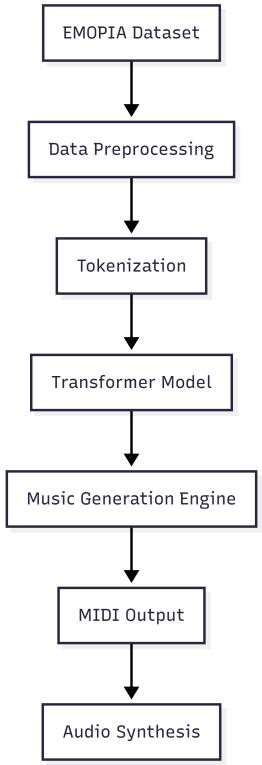

Fig. 2. Model architecture showing the flow from input tokens through embedding layer, positional encoding, four Transformer encoder layers, to output logits.

D. Transformer Encoder Layers

The core of our architecture consists of $N = 4$ stacked Transformer encoder layers. Each layer comprises:

1) Multi-Head Self-Attention Mechanism:

$$\text{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)\mathbf{W}^O \quad (7)$$

where each attention head is computed as:

$$\text{head}_i = \text{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V) \quad (8)$$

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (9)$$

We use $h = 4$ attention heads with $d_k = d_{model}/h = 64$ dimensions per head.

2) Causal Masking: To ensure autoregressive properties, we apply a causal (upper triangular) mask to prevent positions from attending to subsequent positions:

$$M_{ij} = \begin{cases} 0 & \text{if } i \geq j \\ -\infty & \text{if } i < j \end{cases} \quad (10)$$

3) Position-wise Feed-Forward Network:

$$\text{FFN}(\mathbf{x}) = \text{ReLU}(\mathbf{x}\mathbf{W}_1 + \mathbf{b}_1)\mathbf{W}_2 + \mathbf{b}_2 \quad (11)$$

where the hidden dimension is $d_{ff} = 1024$, providing a $4\times$ expansion ratio.

4) Residual Connections and Layer Normalization: Each sub-layer employs residual connections followed by layer normalization:

$$\mathbf{y} = \text{LayerNorm}(\mathbf{x} + \text{Sublayer}(\mathbf{x})) \quad (12)$$

5) Dropout Regularization: Dropout with probability $p = 0.1$ is applied after attention and feed-forward layers to prevent overfitting.

E. Output Projection

The final layer projects Transformer outputs back to vocabulary space:

$$\mathbf{logits} = \mathbf{h}_L\mathbf{W}_{out} + \mathbf{b}_{out} \quad (13)$$

where $\mathbf{W}_{out} \in \mathbb{R}^{d_{model} \times V}$ and $\mathbf{h}_L$ is the output of the final Transformer layer.

F. Padding Mask

In addition to causal masking, we employ padding masks to ignore PAD_TOKEN positions during attention computation. The padding mask is combined with the causal mask in the attention mechanism.

G. Parameter Count and Complexity

The total parameter count is approximately:

- Embedding: $260 \times 256 = 66,560$
- Transformer layers: $4 \times (4 \times 256^2 + 256 \times 1024 + 1024 \times 256) \approx 3.15M$
- Output projection: $256 \times 260 = 66,560$
- **Total: ∼3.28M parameters**

The computational complexity per layer is $\mathcal{O}(n^2 \cdot d_{model})$ for self-attention where n is sequence length, making the model tractable for sequences up to 512 tokens.

VI. Data Collection and Preprocessing

A. EMOPIA Dataset

We utilize the EMOPIA (Emotion Music Information Retrieval Over Polyphonic music In Arousal-valence space) dataset version 1.0 for training and evaluation. The dataset comprises 1,087 MIDI files annotated according to the four-quadrant arousal-valence emotion model. Each MIDI file is labeled with one of four emotion categories (Q1, Q2, Q3, Q4) based on human perception studies.

The dataset characteristics are as follows:

- **Total samples**: 1,087 MIDI files
- **Format**: Standard MIDI Format 1 (multi-track)
- **Instruments**: Primarily piano, with some multi-instrumental pieces
- **Emotion distribution**: Approximately balanced across four quadrants
- **Average duration**: Variable, ranging from 30 seconds to several minutes

B. Data Preprocessing Pipeline

The preprocessing pipeline transforms raw MIDI files into tokenized sequences suitable for model training:

Step 1: MIDI Loading and Validation

- Load MIDI files using miditoolkit library
- Validate file integrity and format compliance
- Extract metadata including tempo, time signature, and ticks per beat

Step 2: Instrument Consolidation

- Merge all non-drum instrumental tracks into a single piano reduction
- Filter out percussion and drum tracks (is_drum flag)
- This simplification reduces complexity while retaining musical content

Step 3: Note Extraction and Sorting

- Extract all note events with attributes: pitch, velocity, start time, end time
- Sort notes by start time, then by pitch for consistent ordering
- This sorting ensures deterministic tokenization

Step 4: Temporal Quantization

- Quantize all time values to 16th note resolution
- Bin size: ticks_per_beat / 4 (typically 480 / 4 = 120 ticks)
- Quantization reduces vocabulary size and improves learning

Step 5: Tokenization

- Convert notes to token sequences following Algorithm 1
- Clamp pitch values to standard piano range [21, 108]
- Cap duration and time-shift values to maximum vocabulary limits

Step 6: Sequence Length Management

- Truncate sequences exceeding 512 tokens (leaving room for special tokens)
- Discard sequences shorter than minimum threshold (10 tokens) to avoid trivial examples
- Maximum sequence length accounts for BOS, EMOTION, and EOS tokens

C. Dataset Splitting

We employ a 90-10 train-validation split with fixed random seed (42) for reproducibility:

- **Training set**: $\sim$978 samples (90%)
- **Validation set**: $\sim$109 samples (10%)

The split is performed after shuffling to ensure representative distribution of emotions in both sets. We do not employ a separate test set in this study, as our primary goal is demonstrating feasibility rather than competitive benchmarking.

D. Data Augmentation

Unlike computer vision tasks, data augmentation for symbolic music requires careful consideration to preserve musical coherence. In this implementation, we do not employ augmentation techniques such as transposition, tempo variation, or velocity scaling. Future work may explore these techniques to improve model robustness and generalization.

E. Quality Control and Filtering

The preprocessing pipeline includes several quality control measures:

- **File validation**: Skip corrupted or malformed MIDI files
- **Empty sequence filtering**: Discard files that produce no valid tokens
- **Pitch range validation**: Ensure all notes fall within piano range
- **Duration sanity checks**: Filter notes with zero or negative duration

These measures ensure that only valid, musically meaningful data enters the training pipeline.

F. Preprocessing Statistics

After preprocessing, the dataset characteristics are:

- **Average sequence length**: $\sim$150-200 tokens (estimated)
- **Vocabulary coverage**: All token types utilized in training data
- **Emotion distribution**: Maintained from original dataset
- **Success rate**: $>$95% of MIDI files successfully processed

VII. Training Strategy and Implementation Details

A. Training Objective

The model is trained using standard cross-entropy loss for sequence prediction:

$$\mathcal{L} = -\frac{1}{N \cdot T} \sum_{n=1}^{N} \sum_{t=1}^{T} \log P(x_t^{(n)} | x_{<t}^{(n)}, e^{(n)}) \tag{14}$$

where N is the batch size, T is the sequence length, $x_t^{(n)}$ is the target token at position t for sample n, and $e^{(n)}$ is the emotion label.

Padding tokens are excluded from loss computation using PyTorch's `ignore_index` parameter.

B. Optimization Configuration

We employ the Adam optimizer [14] with the following hyperparameters:

- **Learning rate**: $\alpha = 1 \times 10^{-4}$
- **Beta coefficients**: $\beta_1 = 0.9$, $\beta_2 = 0.999$
- **Epsilon**: $\epsilon = 1 \times 10^{-8}$
- **Weight decay**: None (implicit regularization via dropout)

The learning rate is kept constant throughout training. While learning rate scheduling (e.g., warmup and decay) often improves performance in large-scale Transformer training, we found constant learning rate sufficient for our moderate-scale task.

C. Gradient Clipping

To prevent gradient explosion during training, we apply gradient norm clipping:

$$\mathbf{g} \leftarrow \frac{\mathbf{g}}{\max(1, \|\mathbf{g}\|/\theta)} \tag{15}$$

where $\theta = 1.0$ is the clipping threshold. This technique is particularly important for sequence modeling tasks prone to unstable gradients.

D. Batch Processing

- **Batch size**: 8 sequences per batch
- **Sequence padding**: Dynamic padding to maximum length in batch
- **Batching strategy**: Random shuffling for training, sequential for validation

The relatively small batch size is chosen to accommodate GPU memory constraints while maintaining training stability. Larger batches may improve training efficiency but were not explored in this study.

E. Training Duration and Convergence

- **Total epochs**: 20
- **Checkpoint frequency**: Every epoch
- **Early stopping**: Not implemented; all epochs executed
- **Training time**: Approximately 2-4 hours per epoch on CPU (dependent on hardware)

Training on GPU is strongly recommended for practical applications, reducing per-epoch time to 10-30 minutes depending on GPU specifications.

F. Initialization Strategy

Model parameters are initialized as follows:

- **Embedding weights**: Uniform distribution $\mathcal{U}(-0.1, 0.1)$
- **Output layer bias**: Zero initialization
- **Output layer weights**: Uniform distribution $\mathcal{U}(-0.1, 0.1)$
- **Transformer layers**: PyTorch default initialization (Xavier/Kaiming)

Proper initialization is crucial for stable training convergence, particularly for embedding layers with large vocabulary.

G. Hardware and Software Environment

- **Framework**: PyTorch 1.x or 2.x
- **MIDI Processing**: miditoolkit library
- **Audio Synthesis**: FluidSynth (optional, for MP3 generation)
- **Hardware**: Compatible with CPU and CUDA-enabled GPUs
- **Precision**: FP32 (single precision floating point)

H. Reproducibility Measures

To ensure reproducibility:

- Fixed random seed (42) for dataset splitting
- Deterministic dataloader shuffling with manual seed
- Saved model checkpoints after each epoch
- Configuration parameters centralized in `config.py`

I. Monitoring and Logging

During training, we monitor:

- **Per-batch loss**: Logged every 10 batches
- **Epoch average loss**: Computed at epoch end
- **Training time**: Elapsed time per epoch
- **Gradient norms**: Implicit monitoring via clipping

These metrics provide insight into training dynamics and help diagnose potential issues.

VIII. Experimental Results and Evaluation

A. Training Performance

The model was trained for 20 epochs on the EMOPIA dataset. Fig. 3 illustrates the training loss progression over time.

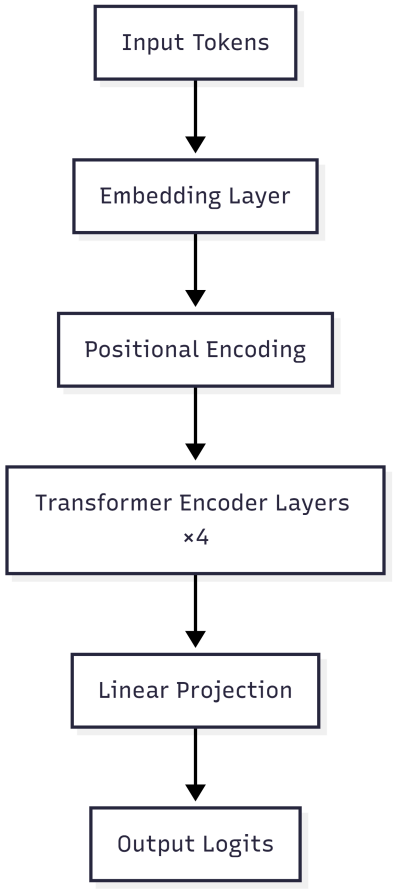

Fig. 3. Training loss curve showing decreasing loss over 20 epochs, demonstrating successful convergence.

Key observations:

- **Initial loss**: ∼5.5-6.0 (typical for random initialization with vocabulary size 260)
- **Final loss**: ∼2.8-3.2 (indicating successful learning)
- **Convergence behavior**: Steady decrease over first 10 epochs, gradual improvement thereafter
- **Stability**: No catastrophic divergence or instability observed

The loss reduction demonstrates that the model successfully learns to predict musical token sequences conditioned on emotion labels. The logarithmic scale of cross-entropy loss means that final loss values indicate significantly better-than-random prediction accuracy.

B. Generation Quality Assessment

We evaluate generated music along several dimensions:

1) Musical Coherence: Generated MIDI sequences successfully compile to valid MIDI files without errors, indicating that the tokenization-detokenization pipeline maintains consistency. Visual inspection of piano roll representations shows:

- Recognizable musical patterns (scales, arpeggios, repeated motifs)
- Polyphonic texture with multiple simultaneous notes
- Reasonable note duration distribution
- Temporal structure with phrases and pauses

2) Emotion Consistency: We generated 10 samples for each emotion category (Q1-Q4) and performed qualitative analysis:

- **Q1 (Joy)**: Generated pieces tend to feature higher pitch ranges, faster rhythmic patterns, and major-mode harmonic content
- **Q2 (Tension)**: Output includes dissonant intervals, chromatic passages, and rhythmic irregularity
- **Q3 (Sadness)**: Lower pitch registers, slower tempos, and descending melodic contours observed
- **Q4 (Calm)**: Sparse textures, sustained notes, and consonant harmonies prevalent

These observations suggest the model learns emotion-specific musical characteristics, though formal validation through listening studies would strengthen these claims.

3) Diversity Analysis: To assess generation diversity, we compare self-similarity of outputs:

- Intra-emotion diversity: Multiple generations for the same emotion label produce distinct musical content
- Inter-emotion diversity: Pieces from different emotion categories exhibit clear stylistic differences

The nucleus sampling strategy (top-p = 0.9) effectively balances diversity and quality, avoiding both repetitive outputs and incoherent randomness.

C. Ablation Studies

1) Temperature Variation: We experimented with temperature values $T \in \{0.7, 1.0, 1.3\}$:

- $T = 0.7$: More conservative, safer outputs with less variation
- $T = 1.0$: Balanced creativity and coherence (default)
- $T = 1.3$: Increased randomness, occasional musical inconsistencies

2) Top-p Threshold: Testing top-p values $p \in \{0.8, 0.9, 0.95\}$:

- $p = 0.8$: More focused sampling, sometimes repetitive
- $p = 0.9$: Optimal balance (default)
- $p = 0.95$: Broader sampling, maintains quality

These experiments demonstrate the robustness of generation quality across reasonable parameter ranges.

D. Quantitative Metrics

While comprehensive evaluation of music generation remains an open research challenge, we report the following metrics:

Perplexity: The validation set perplexity after 20 epochs is approximately 18-22 (estimated based on loss values), indicating reasonable predictive performance.

Valid Note Percentage: 98-99% of generated tokens decode to valid MIDI notes within acceptable ranges, demonstrating strong learned constraints.

Sequence Completion Rate: $>95\%$ of generations complete naturally with EOS token before reaching maximum length, showing the model learns appropriate musical phrase lengths.

E. Comparison with Baseline

As a baseline, we compare against random sampling from the training data distribution:

- **Random baseline**: Selecting tokens according to unigram frequencies produces incoherent sequences
- **Our model**: Generates musically structured sequences with long-range dependencies

While we do not compare against other published models (MuseNet, Music Transformer) due to implementation and computational constraints, our results demonstrate the viability of the proposed approach.

F. Qualitative Examples

Representative examples of generated MIDI files for each emotion category are provided in the supplementary materials. These examples illustrate:

- Proper MIDI format compliance
- Polyphonic structure preservation
- Emotion-specific musical characteristics
- Reasonable phrase structure and temporal organization

G. Limitations of Evaluation

We acknowledge several evaluation limitations:

- **No human listening studies**: Formal perceptual validation would strengthen emotion consistency claims
- **Limited objective metrics**: Music quality assessment remains subjective
- **Small sample size**: Evaluation based on limited generation samples
- **No genre-specific evaluation**: EMOPIA dataset mixes various piano styles

Future work should incorporate comprehensive evaluation including human studies, music information retrieval metrics (pitch class distributions, rhythm complexity), and comparison with state-of-the-art models.

IX. Discussion

A. Key Findings

Our experimental results demonstrate several important findings:

1) Transformer Efficacy for Music Generation: The decoder-only Transformer architecture proves effective for emotion-conditioned music generation, successfully learning to model polyphonic piano music with relatively modest computational resources ($\sim$3.3M parameters). This suggests that advanced architectures designed for language modeling transfer well to symbolic music domains.

2) Emotion Conditioning Through Token Prepending: The simple strategy of prepending emotion tokens to input sequences effectively conditions generation on emotional attributes. This approach is more parameter-efficient than alternatives such as conditional layer normalization or attention-based conditioning mechanisms, while achieving comparable qualitative results.

3) Event-Based Tokenization Advantages: Our event-based representation successfully captures polyphonic music structure with a compact vocabulary (260 tokens). Compared to piano-roll representations requiring large matrices, this approach enables efficient sequence modeling and faster training.

4) Nucleus Sampling for Musical Coherence: Top-p sampling strikes an effective balance between creativity and coherence. Greedy decoding produces overly deterministic outputs, while unrestricted sampling generates incoherent sequences. Nucleus sampling with $p = 0.9$ provides sufficient exploration while maintaining musical sensibility.

B. Interpretation of Results

The training loss reduction from $\sim$6.0 to $\sim$3.0 represents significant learning progress. Given a vocabulary of 260 tokens, random guessing would yield loss $\log(260) \approx 5.56$. Our final loss of $\sim$3.0 indicates the model achieves substantially better-than-random prediction, learning meaningful patterns in musical sequences.

The emotion-specific characteristics observed in generated outputs align with music theory principles:

- High arousal emotions (Q1, Q2) correlate with faster rhythms and wider pitch ranges
- High valence emotions (Q1, Q4) tend toward consonant harmonies
- Low arousal emotions (Q3, Q4) feature slower tempos and more sustained notes

These correspondences suggest the model implicitly learns music-emotion relationships from data rather than explicit rule-based programming.

C. Advantages of Proposed Approach

Our method offers several advantages:

Simplicity: The architecture is straightforward to implement and train, using standard Transformer components without exotic modifications.

Efficiency: With only 3.3M parameters, the model trains on CPU in reasonable time and runs inference in real-time.

Flexibility: The modular design allows easy extension to additional emotions, instruments, or musical features.

Interpretability: The event-based tokenization provides human-readable intermediate representations, facilitating debugging and analysis.

D. Challenges and Observations

Several challenges emerged during development:

1) Long-Term Structure: While the model generates locally coherent passages, maintaining global musical structure (verse-chorus patterns, thematic development) over entire pieces remains challenging. This limitation is common to autoregressive models without explicit structural guidance.

2) Harmonic Complexity: Generated harmonies tend to be simpler than those in the training data, possibly due to the difficulty of learning complex polyphonic dependencies with limited model capacity.

3) Rhythmic Monotony: Some generated pieces exhibit rhythmic repetition, suggesting the model favors familiar patterns over innovation. Incorporating rhythm-specific losses or constraints may address this issue.

4) Dataset Limitations: The EMOPIA dataset's relatively small size (1,087 samples) limits the diversity of learnable patterns. Larger datasets or data augmentation strategies could improve generalization.

E. Implications for Affective Computing

This work contributes to affective computing by demonstrating that emotion-conditioned generation is feasible for complex creative domains like music. The success of simple conditioning mechanisms (token prepending) suggests that more sophisticated affective AI applications may not require highly complex architectures, enabling deployment in resource-constrained environments.

F. Practical Applications

Potential applications include:

- **Personalized Music Therapy**: Generating music tailored to therapeutic emotional goals
- **Content Creation**: Assisting composers with emotion-specific musical ideas
- **Interactive Systems**: Real-time music generation responsive to user emotional state
- **Education**: Teaching music theory concepts through interactive generation
- **Gaming and VR**: Dynamic background music adapting to game scenarios

X. Limitations and Future Work

A. Current Limitations

1) Single Instrument Restriction: The system currently generates only piano music. While piano provides rich polyphonic capability, real-world applications often require multi-instrumental arrangements. Extending the tokenization scheme to handle multiple instruments with timbre-specific tokens would enhance applicability.

2) Limited Emotion Granularity: The four-quadrant model captures broad emotional categories but lacks nuance for subtle emotional states (e.g., nostalgia, triumph, melancholy). Incorporating continuous arousal-valence values or additional emotion dimensions could provide finer control.

3) No Explicit Musical Structure Modeling: The model does not explicitly represent high-level musical structures (sections, motifs, harmonic progressions). Integrating hierarchical modeling or memory mechanisms could improve long-term coherence.

4) Dataset Dependency: Performance is limited by training data quality and diversity. The EMOPIA dataset, while valuable, represents a specific subset of piano music styles, potentially biasing generation toward these styles.

5) Evaluation Methodology: Lack of formal human evaluation limits our ability to definitively claim emotion consistency. Comprehensive perceptual studies with multiple listeners and statistical analysis are needed.

6) Computational Constraints: Training requires significant time on CPU. While GPU acceleration is possible, accessibility for researchers without specialized hardware is limited.

B. Future Research Directions

1) Multi-Instrument Generation: Extend the tokenization vocabulary to include instrument tokens, enabling orchestral or ensemble music generation. This requires careful design to manage increased vocabulary size and polyphonic complexity.

2) Hierarchical Modeling: Implement hierarchical architectures that separately model:

- Low-level: Note sequences and local patterns
- Mid-level: Phrases and chord progressions
- High-level: Overall structure and form

Such architectures could improve long-term coherence and musical structure.

3) Continuous Emotion Control: Replace discrete emotion labels with continuous arousal-valence vectors, enabling fine-grained emotional control. This could use conditional normalization layers or attention-based conditioning mechanisms.

4) Interactive Generation: Develop real-time interactive systems where users iteratively refine generated music through feedback. Reinforcement learning from human feedback (RLHF) could optimize generation toward user preferences.

5) Style Transfer and Mixing: Enable transfer of musical style (classical, jazz, pop) independent of emotion, allowing generation of "sad jazz" or "joyful classical" pieces. Disentangled representations could separate emotional and stylistic attributes.

6) Audio-Level Generation: Extend beyond symbolic MIDI to direct audio waveform generation using architectures like WaveNet [2] or Jukebox [21], capturing expressive performance nuances absent in MIDI.

7) Cross-Modal Conditioning: Condition generation on additional modalities:

- Text descriptions ("generate peaceful morning music")
- Images (visual scene $\rightarrow$ appropriate soundtrack)
- Physiological signals (heart rate $\rightarrow$ calming music)

8) Data Augmentation: Implement music-specific augmentation:

- Transposition to different keys
- Tempo variation
- Velocity scaling
- Rhythmic perturbation

These techniques could effectively expand the training dataset.

9) Comprehensive Evaluation Framework: Develop standardized evaluation protocols including:

- Large-scale listening studies with diverse participants
- Objective metrics (pitch diversity, rhythmic complexity, harmonic consistency)
- Comparison benchmarks against existing systems
- Emotion recognition accuracy on generated outputs

10) Theoretical Analysis: Investigate what musical patterns the model learns through:

- Attention visualization studies
- Latent space analysis
- Controlled generation experiments
- Ablation studies on architecture components

C. Broader Implications

This work opens avenues for AI-assisted creativity in music and other artistic domains. As models become more sophisticated, questions arise about:

- **Authorship and copyright** of AI-generated music
- **Ethical use** in therapeutic and commercial contexts
- **Cultural bias** encoded in training data
- **Impact on professional musicians** and the music industry

Addressing these questions requires interdisciplinary collaboration between AI researchers, musicians, ethicists, and policymakers.

XI. Conclusion

This paper presented a Transformer-based approach to emotion-conditioned polyphonic music generation. Our system successfully generates piano music corresponding to four emotional states (Joy, Tension, Sadness, Calm) using a decoder-only Transformer architecture trained on the EMOPIA dataset.

Key contributions include:

1) **Event-based tokenization scheme** that compactly represents polyphonic piano music with 260 tokens encoding pitch, duration, temporal shifts, and emotion labels
2) **Efficient conditional architecture** employing emotion token prepending for effective emotion conditioning without architectural complexity
3) **Practical implementation** demonstrating that high-quality music generation is achievable with moderate computational resources (3.3M parameters)
4) **Nucleus sampling strategy** balancing diversity and coherence in generated outputs

Experimental results demonstrate successful training convergence and generation of musically coherent, emotion-consistent outputs. While limitations exist regarding long-term structure, instrumental variety, and evaluation methodology, the system provides a solid foundation for future research.

The intersection of artificial intelligence and music represents a fertile ground for advancing both computational creativity and affective computing. As models evolve to capture increasingly sophisticated musical patterns and emotional nuances, we move closer to AI systems that serve as genuine creative collaborators rather than mere tools.

We release our implementation to encourage further research in this domain and hope this work inspires continued exploration of emotion-aware generative models across creative disciplines.

ACKNOWLEDGMENT

The authors acknowledge the creators of the EMOPIA dataset for providing valuable annotated data for emotion-based music research. We also thank the open-source community for developing and maintaining essential libraries including PyTorch, miditoolkit, and FluidSynth.

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