LEARNING MUSIC STYLE FOR PIANO ARRANGEMENT THROUGH CROSS-MODAL BOOTSTRAPPING

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ABSTRACT

What is music style? Though often described using text labels such as "swing," "classical," or "emotional," the real style remains implicit and hidden in concrete music examples. In this paper, we introduce a cross-modal framework that learns implicit music styles from raw audio and applies the styles to symbolic music generation. Inspired by BLIP-2, our model leverages a Querying Transformer (Q-Former) to extract style representations from a large, pre-trained audio language model (LM), and further applies them to condition a symbolic LM for generating piano arrangements. We adopt a two-stage training strategy: contrastive learning to align auditory style with symbolic expression, followed by generative modelling to perform music arrangement. Our model generates piano performances jointly conditioned on a lead sheet (content) and a reference audio example (style), enabling controllable and stylistically faithful arrangement. Experiments demonstrate the effectiveness of our approach in piano cover generation, style transfer, and audio-to-MIDI retrieval, achieving substantial improvements in style-aware alignment and music quality.[1]

1 INTRODUCTION

Automatic music generation is often controlled by *explicit* content such as melody, chords, and text labels (Yang et al., 2019; Wang et al., 2020b; Lu et al., 2023; Bhandari et al., 2025), but music concepts can be more nuanced than we often realize. When musicians learn a style, instead of relying on abstract definitions like "romantic" or "jazz" alone, they absorb patterns from music examples that share common stylistic traits. The commonality across these examples forms a style, an *implicit* one that cannot be fully described with words or labels but only understood through the music itself. This paper explores how such implicit style can be internalized from music examples and used to control music generation in a deep learning framework.

Large-scale music language models (music LMs) have shown strong capabilities in learning explicit music content, as demonstrated by probing studies (Wei et al., 2024; Ma & Xia, 2024; Ma et al., 2024; Vásquez et al., 2024; Castellon et al., 2021) and adapter-based designs (Lin et al., 2024a; Zhang et al., 2024; Lin et al., 2024b; Wu et al., 2024). Yet, control over implicit style remains limited. For example, when using audio to guide symbolic music generation, existing models can extract melody and chords (Donahue et al., 2022; Wang et al., 2022), but capturing stylistic traits like comping patterns or voicing preferences remains a greater challenge. This requires disentangling style from music content, which current music LM-based studies have yet to explore.

In this paper, we explore learning implicit music style in a cross-modal setting for symbolic piano arrangement. Our goal is to generate an arrangement conditioned on two inputs: an audio example (providing style) and a lead sheet (melody and chords as content). To achieve this, we connect pre-trained music LMs in the audio and symbolic domains using a Querying Transformer (Q-Former), a lightweight Transformer originally designed for vision-language alignment (Li et al., 2023). As shown in Figure 1, we extend its role to capture implicit music style, extracting a *style representation* from the hidden states of an audio LM. A symbolic LM then conditions on this representation, along with the *content* of the lead sheet, to generate an arrangement. The Q-Former enables style transfer between two large unimodal LMs without re-training them—a process we refer to as *bootstrapping*.

[1] Demo page: `https://anonymous55aht.github.io/`

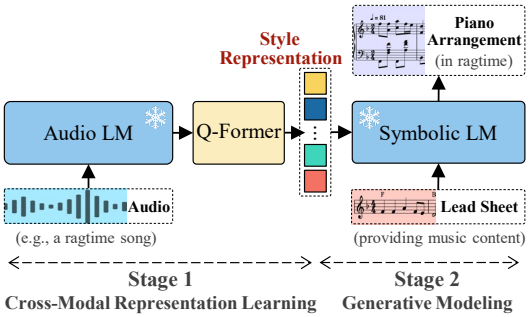


Figure 1: A Q-Former module bridges the modality gap between a frozen audio LM and a symbolic music LM. It extracts cross-modal music *style* from the hidden representations of the audio LM and, together with a lead sheet providing music *content*, conditions the symbolic LM for piano arrangement. The Q-Former is trained in a two-stage process, effectively bootstrapping audio-to-symbolic arrangement without re-training either LM backbone.

In our design, we treat the Q-Former as a bottleneck to transfer only style-related information and adopt a two-stage training strategy. The first stage employs contrastive learning, training the Q-Former to extract auditory representations that are musically relevant, expressible in symbolic piano composition, and independent of explicit music content. The second stage focuses on generative modeling, where the Q-Former's output conditions the symbolic LM to arrange the desired piano performance. We show that the complete system generates more stylistically accurate cover songs compared to existing audio-to-symbolic arrangement methods, while also enabling piano style transfer by conditioning on audio examples. In addition, we demonstrate that the Q-Former can also be applied to audio-to-symbolic retrieval, further highlighting its strength as a general-purpose cross-modal representation learner.

In summary, the contributions of this paper are threefold:

1. We use the Q-Former to **align audio and symbolic modalities through implicit music style**, extending its role beyond content alignment in vision-language tasks.
2. We present **a new methodology to disentangle music style from large, pre-trained LMs**, offering a more scalable alternative to traditional latent-variable disentanglement methods.
3. Our model achieves **style-aware audio-to-symbolic piano cover arrangement**. Experiments demonstrate that it outperforms existing audio-to-symbolic models, including both disentanglement-based methods and standard LM approaches.

2 Related Works

We review two areas of key relevance. Section 2.1 discusses recent advances in LMs for music generation. Section 2.2 focuses on piano cover generation, the primary task addressed in this paper.

2.1 Music Language Models

Rapid progress in large-scale language models has transformed how we interact with various forms of media, including text, image, and music (Touvron et al., 2023; Alayrac et al., 2022; Li et al., 2023; Kong et al., 2024; Yuan et al., 2025). In particular, large music LMs (Agostinelli et al., 2023; Melechovský et al., 2024; Thickstun et al., 2024; Bhandari et al., 2025) have notably influenced creative practices and user experiences. Models like MusicGen (Copet et al., 2023) can generate music audio with rich timbres directly from text, while MuseCoco (Lu et al., 2023) produces symbolic compositions with well-structured textures in varied genres. These advancements are driven by training large-scale neural networks on extensive data, scaling up to billions of model parameters to enhance controllability and musicality.

Despite these successes, most existing music LMs operate in an unimodal setting, focusing solely on either audio or symbolic representations. Although text-to-music generation has been increasingly

effective (Agostinelli et al., 2023; Melechovský et al., 2024; Bhandari et al., 2025), text descriptions may fall short in expressing nuanced style or performance subtlety. In contrast, our work explores a cross-modal framework that bridges audio and symbolic modalities. By leveraging the strong perceptual understanding of audio LMs and the expressive composition capabilities of symbolic LMs, we bootstrap a system for audio-to-symbolic arrangement. This approach enables more intuitive and fine-grained control over music style beyond what can be conveyed through text alone.

2.2 Piano Cover Generation

Piano cover generation aims to reinterpret an audio recording as a symbolic piano performance. Unlike traditional music transcription, which primarily analyses note-level content such as pitch and timing (Kong et al., 2021; Ou et al., 2022; Gardner et al., 2022; Gu et al., 2024; Zeng et al., 2024), a piano cover often targets higher-level, more structured music elements that shape the *feel* of a performance. The goal is to generate symbolic arrangements that not only sound correct but also feel musically aligned with the original audio.

Existing approaches to piano cover generation often leverage pre-trained transcription models, primarily extracting melodic and harmonic content from the audio (Nakamura & Yoshii, 2018; Tan et al., 2024b;a; Wang et al., 2022; Choi & Lee, 2023). However, such models tend to overlook stylistic nuances, resulting in outputs accurate in harmony but lacking the expressive character of the source performance. In this paper, we re-frame piano cover generation through the lens of content-style disentanglement, acquiring *content* in the symbolic form (i.e., melody and chord progression) while learning *style* from the audio. This approach bridges the audio-symbolic gap more effectively, capturing not just *what* is played, but *how* it is played.

3 Method

Our goal is to learn music style representations from the audio and leverage these representations to arrange symbolic piano performances. To bridge the modality gap from audio to symbolic music, we adopt the Q-Former (Li et al., 2023) under a two-stage training strategy. As shown in Figure 2, Stage 1 focuses on audio-symbolic representation learning with a frozen audio LM, while Stage 2 addresses audio-to-symbolic arrangement with a symbolic LM. In Section 3.1, we first introduce our audio-symbolic data pairing method that facilitates style learning. We illustrate the Q-Former architecture in Section 3.2, followed by the two-stage training procedure in Sections 3.3 and 3.4.

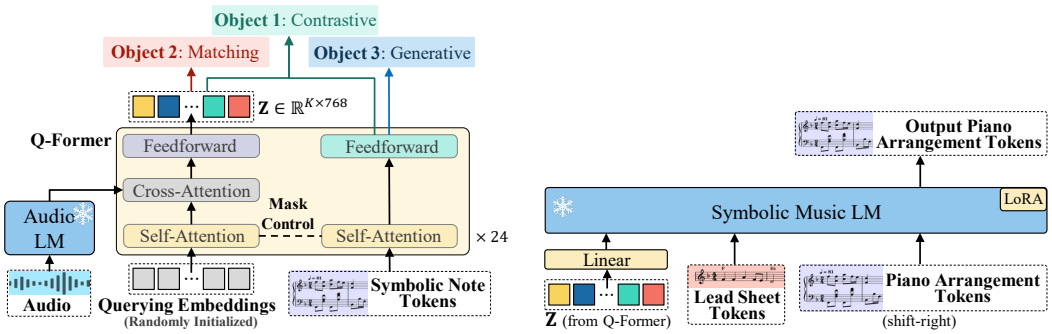
3.1 Data Pairing for Style Learning

Training an audio-to-symbolic alignment model requires paired audio–MIDI data. In this work, we use 10-second audio clips paired with 4-bar MIDI segments. Since our goal is to capture style rather than low-level note transcription, we construct the pairs to be *loosely aligned*. Specifically, for each audio clip, we select a MIDI segment near its center with a random temporal shift of up to ± 1 second, and we randomly transpose the MIDI into all 12 keys. This design assumes that musical style is locally consistent, while discouraging the model from memorizing exact note-to-note correspondences. In the following sections, we show that the two-step training method enables the model to abstract style features that are shared between the modalities.

We represent music audio as raw waveforms sampled at 32kHz. MIDI is tokenized into note event sequences quantized at 1/12-beat resolution. We include various symbolic features including time signature (quadruple and triple meters), tempo curve, note pitch, duration, and velocity.

3.2 Q-Former Architecture

The Q-Former is a Transformer encoder with two parallel, modality-specific streams that share the self-attention layers. As shown in Figure 2a, it accepts audio and symbolic inputs and learns a cross-modal music style representation. The left stream interacts with the audio LM to extract auditory music features. The right stream encodes symbolic music tokens. A set of querying embeddings (*queries*), randomly initialized, is fed to the left stream and serves as the bridge between the two modalities. At test time, the left stream is retained to extract cross-modal style directly from audio.



(a) Stage 1: Cross-modal learning with Q-Former.

(b) Stage 2: Audio-to-symbolic arrangement.

Figure 2: Overview of the two-stage framework. (Left) Stage 1: The Q-Former is a Transformer encoder with two parallel, modality-specific streams (audio and symbolic). Both streams are used during training for cross-modal alignment, while only the audio stream is retained at test time. It extracts a cross-modal music style representation $\mathbf{Z}$ via cross-attention to an audio LM. (Right) Stage 2: A symbolic music LM further generates piano arrangements conditioned on (i) the style embedding $\mathbf{Z}$ obtained from the Q-Former and (ii) a lead sheet providing music content.

We initialise the Q-Former weights using the pre-trained MusicBERT-Base model (Zeng et al., 2021). The added cross-attention layers are randomly initialised. Following Blip-2 (Li et al., 2023), we use 32 queries with dimension 768. Symbolic notes are embedded in the OctMIDI format (Zeng et al., 2021), which learns a joint note-wise embedding by summing up the embeddings of individual note attributes. Overall, the Q-Former comprises 186M parameters, including the learnable queries and symbolic note embeddings.

3.3 Stage 1: Audio-Symbolic Representation Learning

We integrate the Q-Former into MusicGen Copet et al. (2023), one of the leading audio LMs available today. The queries interact with audio hidden states through cross-attention while remaining connected to the symbolic stream via shared self-attention layers. However, relying solely on loosely aligned data is insufficient for learning robust style representations, since no direct *content*-level correspondence exists between the audio and symbolic streams (see Section 3.1). To prevent representation collapse and encourage meaningful style abstraction, we introduce three complementary training losses, each paired with a tailored self-attention mask that regulates cross-modal interactions. These objectives are illustrated in Figure 2a and detailed below.

The primary objective is **Audio-Symbolic Contrastive Learning**, which enforces a higher audio-symbolic similarity for positive pairs (i.e., originally aligned pairs) compared to negative ones (i.e., randomly paired audio and MIDI clips). Let $\mathbf{Z} \in \mathbb{R}^{32\times768}$ be the query outputs from the audio stream of Q-Former, and $t \in \mathbb{R}^{1\times768}$ be the output embedding of the start token (<s>) from the symbolic stream. We define the audio-symbolic similarity as $\max_k(\cos(\mathbf{Z}_k, t))$ for $k = 1, 2, \cdots, 32$, where $\cos(\cdot,\cdot)$ denotes the cosine similarity. The contrastive loss pulls closer aligned audio and symbolic clips in the representation space, while pushing apart unrelated pairs. To prevent information leakage, we employ a *unimodal self-attention mask*, ensuring queries and symbolic notes do not attend to each other. For detailed mask design, we refer readers to BLIP-2 (Li et al., 2023).

The second objective is **Audio-Symbolic Matching**. It is formulated as a binary classification task, where the model predicts whether a given audio-symbolic pair corresponds to each other. On top of contrastive loss, the matching loss aims to capture a finer cross-modal correspondence. In this case, we apply *no masking*, allowing the queries to attend across modalities. Each query output $\mathbf{Z}_k$ is fed into a binary linear classifier to produce a logit, and the logits from all queries are averaged to compute the final matching score. To create informative negative pairs, we employ the hard negative mining strategy in (Li et al., 2021).

The final objective, **Audio-Grounded Symbolic Generation**, trains the Q-Former to autoregressively generate piano arrangement conditioned on an input audio and lead sheet. We implement a *cross-model causal self-attention mask*, allowing the symbolic notes to see the queries but

not vice versa. This generative loss enforces alignment between the query-extracted auditory style and its symbolic realization. To signify a decoding task, we replace the starting <s> token with a <DEC> token prepended by a sequence of lead sheet note embeddings.

3.4 Stage 2: Audio-to-Symbolic Generative modeling

In the generative modelling stage, we take advantage of the generative capability of MuseCoco (Lu et al., 2023), a large-scale symbolic music LM. As illustrated in Figure 2b, MuseCoco is used to reconstruct a piano arrangement based on two concatenated conditional inputs: 1) the query output embeddings $\mathbf{Z}$ from the Q-Former, and 2) a lead sheet. The Q-Former is pre-trained at Stage 1 to extract cross-modal music style from the audio, thus providing style guidance. The lead sheet defines the theme melody and harmony as the content.

To enable compatibility with MuseCoco, we project $\mathbf{Z}$ into the same embedding dimension as MuseCoco's token embeddings via a linear layer. Symbolic note tokens are converted into the REMI format (Huang & Yang, 2020). Despite the slightly different tokenizations used across stages, we find that the latent representations learned in Stage 1 remain compatible with Stage 2. Since MuseCoco does not natively support lead sheet conditioning, and the inclusion of the lead sheet alters its input format, we insert a LoRA adapter (Hu et al., 2022) of rank 16 into each self-attention layer. This enables the model to reweight attention and incorporate the new conditioning inputs, while keeping MuseCoco itself frozen.

4 Arrangement Demonstration

In this section, before presenting experiments, we first demonstrate the performance of our audio-to-symbolic arrangement model under *freely manipulated* audio style references. Figure 3a shows an 8-bar lead sheet excerpt from the musical *The Sound of Music*. The selected passage features harmonically rich chords, including diminished and seventh chord qualities, which present suitable complexity for arrangement experiments. Figures 3b to 3d showcase the arrangement results conditioned on varied audio references. The 8-bar arrangement is generated using windowed sampling, wherein a 4-bar context window progresses forward every 2 bars and continues sampling conditioned upon the preceding 2 bars.

Figure 3b shows the piano cover from the original *The Sound of Music* soundtrack,[2] which features lush orchestration dominated by string ensembles. Our arrangement captures this orchestral essence through dense, block-chord voicing that emulates the sonority of string sections. Additionally, ornaments such as arpeggios and trills are found to complement the sweeping harmonic textures, which contributes to the music's free-flowing character.

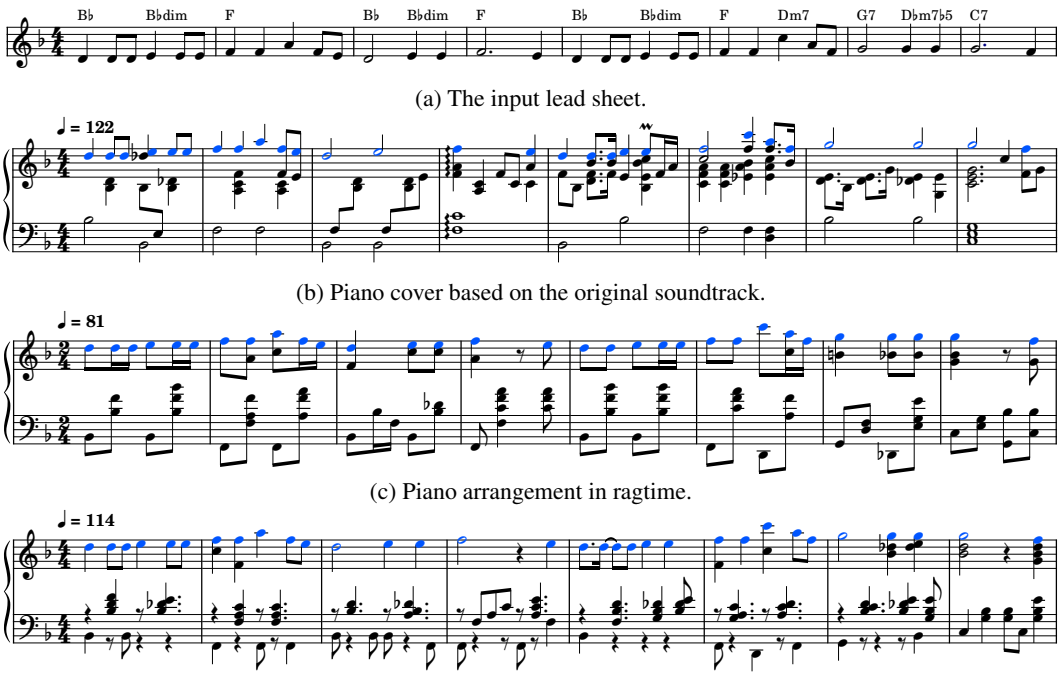
Figure 3c shows an arrangement conditioned on the ragtime classic *The Entertainer*.[3] Following the audio recording, the arrangement's tempo is "not fast," and the piano texture distinctly adopts a ragtime rhythm, featuring steady bass notes on downbeats and syncopated chordal accents on upbeats.

Figure 3d shows an arrangement conditioned on the bossa nova piece *The Girl from Ipanema*.[4] In this interpretation, the arrangement is characterized by a moderate tempo and distinctive left-hand syncopated patterns characteristic of the bossa nova genre.

Across all three piano arrangements, while distinct music styles are effectively captured from the audio references, the theme melody and harmonic structures remain faithfully preserved. In Figure 3, we highlight melody notes preserved from the lead sheet using blue note heads.

Additional examples are available on our demo page, including arrangements in a wider range of classical, jazz, and pop styles applied to well-known lead sheets, illustrating the flexibility of both style and lead sheet control.

[2]Original audio: `https://youtu.be/6f0T6UV-HiI&t=57`
[3]Ragtime audio: `https://youtu.be/jKlfNfRZL9I&t=11`
[4]Bossa nova audio: `https://youtu.be/DvA_wDOVD10&t=12`



(a) The input lead sheet.

(b) Piano cover based on the original soundtrack.

(c) Piano arrangement in ragtime.

(d) Piano arrangement in bossa nova.

Figure 3: Audio-to-symbolic arrangement for an 8-bar excerpt from *The Sound of Music*. Score is manually engraved from MIDI for visualisation purpose. Figures 3b to 3d are arranged based on the lead sheet in 3a and an audio reference from the original soundtrack, a ragtime piece, and a bossa nova piece, respectively. Preserved music contents are highlighted in blue note heads. Synthesized audio is provided on the demo page: `https://anonymous55aht.github.io/`.

5 Experiments

This section evaluates our audio-to-symbolic arrangement model, focusing on whether it can transfer audio-derived style while preserving lead-sheet content. Because there is no established benchmark for measuring audio style in symbolic outputs, we cast evaluation primarily as audio-conditioned *cover song arrangement*, which enables comparison to prior baselines. We hypothesize that stronger style capture improves overall arrangement quality. As a complementary analysis, we further assess the learned audio–symbolic representations via retrieval-based comparisons and ablations.

In Section 5.1, we introduce the datasets used in the experiments. In Section 5.2, we describe the baseline models used for comparison. Our evaluation is divided into two parts: objective evaluation in Section 5.3, and subjective evaluation in Section 5.4. Finally, Section 5.5 extends the evaluation to audio-to-symbolic retrieval, highlighting the Q-Former's broader capability in cross-modal alignment. More details for model configuration and training are covered in the Appendix A.

5.1 Datasets

Our model is trained on two dual-modal datasets: POP909 (Wang et al., 2020a) and PIAST (Bang et al., 2024). POP909 contains 1K piano cover arrangements created by professional musicians. The music genre is primarily Mandarin pop, while the accompanying audio features diverse band instrumentation, which can help the model learn generalizable audio representations of pop music. PIAST, on the other hand, contains 8K piano recordings along with symbolic transcriptions across a variety of genres, including pop, jazz, and classical. Despite the lack of band instrumentation in the piano recording, the genre diversity encourages the model to produce more expressive and stylistically varied performances. We split both datasets at song level into training (90%), validation (5%), and test (5%) sets. Each symbolic MIDI file is clipped into 4-bar segments with a 2-bar hop size, transposed to all 12 keys, and center-aligned with the corresponding 10s audio clip.

Table 1: Objective evaluation on audio-to-symbolic coherence. Ballroom/GTZAN are out-of-distribution sets to assess cross-domain arrangement capabilities.

	POP909		Ballroom/GTZAN	
	Acc@5 (%) ↑	**Rank** ↓	**Acc@5 (%)** ↑	**Rank** ↓
Ours	**27.1** $\pm$ 1.2	**16.3** $\pm$ 0.3	21.4 $\pm$ 0.6	**30.2** $\pm$ 0.3
PCG2	23.6 $\pm$ 1.3	16.7 $\pm$ 0.3	**21.7** $\pm$ 0.9	31.3 $\pm$ 0.6
A2M	18.4 $\pm$ 1.5	18.2 $\pm$ 0.3	19.6 $\pm$ 0.8	30.6 $\pm$ 0.4
w/o PT	24.2 $\pm$ 1.1	16.9 $\pm$ 0.3	18.1 $\pm$ 0.1	33.1 $\pm$ 0.5

We also test on two out-of-domain datasets: Ballroom (Krebs et al., 2013) and GTZAN (Dittmar et al., 2015). Both datasets feature audio recordings with diverse band and orchestral instrumentation, as well as fine-grained music genres such as jive and bossa nova. Since they lack paired symbolic annotations, we use them for testing only. This allows us to assess the model's generalization ability and its capacity to accommodate styles beyond pop music.

5.2 Baseline Models

We compare our model against two representative piano cover generation models: *PiCoGen2* (Tan et al., 2024a) and *Audio-to-MIDI* (Wang et al., 2022), as well as one ablation variant of our method.

PiCoGen2 (PCG2) is a Transformer-based language model that builds on the hidden representations of Sheetsage, which itself is derived from Jukebox (Dhariwal et al., 2020), a large-scale music language model. Leveraging Jukebox's internalized understanding of music *content*, PiCoGen2 generates symbolic piano arrangements directly from audio.

Audio2MIDI (A2M) is a disentanglement framework, using separate modules to extract piano texture and chord from the audio. The texture extractor is initialized from a pre-trained piano transcription model (Hawthorne et al., 2018). The extracted components are then merged to form a piano arrangement.

Ours w/o Pre-Training (w/o PT) is an ablation variant of our model in which the Q-Former is trained directly in Stage 2, without undergoing the representation learning phase in Stage 1. This setup tests the validity of the two-stage training strategy we applied in this work.

To ensure a fair comparison with baseline models, we use Sheetsage (Donahue et al., 2022; Donahue & Liang, 2021) to transcribe lead sheets from the audio, making audio the sole input for all methods.

5.3 Objective Evaluation

We first evaluate our model's performance in terms of *audio-to-symbolic coherence*, specifically assessing how well the generated piano covers preserve the style from the original audio. To do this, we leverage CLaMP3 (Wu et al., 2025) as a cross-modal retriever. For each test audio, CLaMP3 computes the similarity between the audio and all generated symbolic piano covers. If the most similar symbolic candidate corresponds to the one generated from the audio input, we count it as a correct match. Based on this setup, we report two metrics: 1) *Top-5 Retrieval Accuracy* (Acc@5): the proportion of audio inputs for which the correct symbolic output is ranked within the top 5. Higher values indicate stronger coherence; 2) *Mean Rank*: the average rank position of the correct audio-symbolic pair across all candidates. Lower values indicate better alignment.

We consider two evaluation settings: 1) *in-distribution* evaluation on the POP909 dataset, and 2) *out-of-distribution* evaluation on 100 tracks randomly drawn from the Ballroom and GTZAN datasets, which can reflect the model's generalization to unseen genres and instrumentation. We use 16-bar audio excerpts for evaluation on POP909, and full 30s audio clips for Ballroom and GTZAN. Each model is evaluated over 10 independent runs, and we report the mean and standard error. As shown in Table 1, our model consistently outperforms all baselines on POP909 by a clear margin. On the testing-only Ballroom/GTZAN datasets, it also achieves a substantially lower Mean Rank, demonstrating strong generalization across styles and genres. In comparison, the w/o PT variant surpasses PCG2 and A2M on POP909 but fails on Ballroom/GTZAN, confirming that our Q-Former pre-trained at Stage 1 is crucial for effective style transfer and cross-modal piano arrangement.

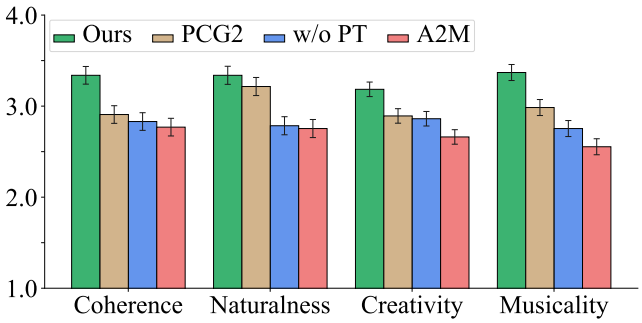


Figure 4: Subjective evaluation on music quality, conducted on Ballroom and GTZAN datasets to assess the musicality for diverse music genres and styles.

5.4 Subjective Evaluation

We further conduct a double-blind online listening survey to evaluate the music quality. The survey comprises 6 test pieces of varied genres drawn from the Ballroom and the GTZAN datasets. Each test piece is accompanied by 4 piano covers interpreted by our model and each baseline model. For each model, we select the best result from 3 generated samples. All samples are 16 bars long and rendered to audio using the Cakewalk TTS-1 soundfont, resulting in ˜40s audio per sample. Both the order of the test pieces and the order of samples are randomized. Participants are asked to complete 3 test pieces by rating each piano cover on a 5-point Likert scale across 4 criteria: 1) *Audio-to-Symbolic Coherence*, 2) *Naturalness*, 3) *Creativity*, and 4) *Overall Musicality*.

A total of 21 participants with diverse musical backgrounds completed our survey. The average completion time is 12 minutes. Figure 4 shows the mean ratings and standard errors analyzed using within-subject ANOVA (Scheffe, 1999). The analysis reveals significant main effects ($p < 0.05$) across all evaluation criteria. While our model performs comparably to the state-of-the-art PCG2 in Naturalness, it consistently receives higher ratings than the baselines across all criteria. A Bonferroni post-hoc test further confirms that our model significantly outperforms all baselines in Coherence and Musicality. These results align with the objective evaluation and demonstrate that our model captures music style more effectively and produces coherent, high-quality piano cover arrangements.

5.5 Evaluation on Audio-to-Symbolic Alignment

While the Q-Former bridges the modality gap for audio-to-symbolic arrangement, it can also operate independently as an audio-to-symbolic retriever. In this setting, the Q-Former measures stylistic coherence between an audio clip and a symbolic segment by comparing their learned representations. Given an audio query and a set of symbolic candidates, the model can retrieve the symbolic piece that best aligns with the music style of the query audio. To the best of our knowledge, CLaMP3 (Wu et al., 2025) is the only existing model with an audio-to-symbolic alignment capability, and we aim to evaluate whether our approach can achieve superior performance.

5.5.1 Audio-to-Symbolic Retrieval

To assess the alignment capability of the Q-Former, we evaluate it after Stage-1 training on the audio-to-MIDI retrieval task. In each of 10 independent runs, we construct a test set of 128 pairs of 10-second audio and 4-bar MIDI, randomly sampled from PIAST and POP909 (64 pairs each). For each audio query, the model is tasked with retrieving its corresponding MIDI segment from the full pool of 128 candidates. We consider two evaluation settings: one in which MIDI candidates are randomly transposed to all 12 keys, and the other without transposition. This setup helps us examine the model's robustness in capturing stylistic features beyond absolute pitch and key. Performance is measured using three metrics: Top-1 Accuracy (Acc@1), Top-5 Accuracy (Acc@5), and Mean Rank. We report the mean and standard error across the 10 resampled runs.

As shown in Table 2, we compare our model against CLaMP3 in addition to a random guessing bot for sanity check. In CLaMP3, audio and MIDI are aligned indirectly via text due to the greater

Table 2: Objective evaluation on audio-to-MIDI retrieval. Results are compared against baseline models and across two evaluation settings: MIDI with random transposition (left) and without transposition (right), highlighting robustness in capturing stylistic features beyond absolute pitch and key.

	w/o Transposition			w/ Random Transposition		
	Acc@1 (%) ↑	**Acc@5 (%)** ↑	**Rank** ↑	**Acc@1 (%)** ↑	**Acc@5 (%)** ↑	**Rank** ↑
Random	1.4 ± 0.3	4.8 ± 0.8	64.4 ± 1.7	0.7 ± 0.2	4.2 ± 0.5	65.4 ± 1.0
CLaMP	3.4 ± 0.4	15.0 ± 0.6	42.5 ± 0.2	3.4 ± 0.4	11.0 ± 0.6	48.5 ± 0.3
Ours	**71.4** ± 1.5	**95.1** ± 0.5	**2.1** ± 0.1	**70.2** ± 1.5	**94.8** ± 0.5	**2.1** ± 0.1

Table 3: Ablation study on individual pre-training objectives for cross-modal alignment.

	PIAST		POP909	
	Acc@1 ↑	**Rank** ↓	**Acc@1** ↑	**Rank** ↓
C	96.7 ± 0.3	1.8 ± 0.2	36.2 ± 1.3	5.2 ± 0.3
C+M	**97.2** ± 0.4	**1.6** ± 0.2	40.8 ± 0.9	5.0 ± 0.4
C+M+G	97.1 ± 0.3	1.7 ± 0.2	**44.7** ± 1.4	**4.7** ± 0.4

availability of music–text pairs in both domains. While this indirect alignment allows CLaMP3 to perform substantially better than random guessing, its Top-1 accuracy remains low. Interestingly, transposing the MIDI candidates has a noticeable effect, leading to a 4-point drop in Acc@5 and a 6-rank increase in Mean Rank. We presume this is because key signatures are frequently referenced in text descriptions of music, making CLaMP3 particularly sensitive to pitch-level features while struggling to capture finer stylistic nuances. In comparison, our model consistently outperforms CLaMP3 across all metrics and exhibits negligible performance differences between the transposed and non-transposed settings. This demonstrates that our Q-Former learns more robust audio-to-symbolic alignments, effectively capturing stylistic coherence beyond surface-level attributes.

5.5.2 Ablation Study on Pre-Training Objectives

We are also interested in the contribution of each pre-training objective in Section 3.3 to cross-modal alignment. We conduct an ablation study on the Q-Former's audio-to-MIDI retrieval performance based on three different pre-training configurations: contrastive loss only (**C**), contrastive + matching losses (**C+M**), and contrastive + matching + generative losses (**C+M+G**). As in the previous section, we repeat our experiment over 10 independent runs on 128 resampled audio-MIDI pairs.

As shown in Table 3, we conduct evaluation separately on PIAST and POP909. The former involves piano-only music, while the latter includes multi-instrumental accompaniments, requiring the model to extract style from richer audio textures. We observe that the performance difference is relatively small on PIAST, suggesting that contrastive learning alone may suffice for simpler piano alignment. However, on POP909, we see both the matching and generative losses contribute meaningfully to improved retrieval accuracy and lower mean rank. These findings indicate that all three objectives are important for learning robust, generalizable cross-modal alignment.

6 Conclusion

In this paper, we introduce a cross-modal framework for audio-to-symbolic arrangement. By repurposing the Q-Former to align audio and symbolic modalities, our model extracts and applies implicit music style using pre-trained music LMs, enabling expressive piano arrangement conditioned on both a lead sheet and an audio reference. Through a two-stage training process—combining representation learning and generative modeling—we extract stylistic features from a frozen, large audio LM and guide a symbolic LM without re-training either backbone. We conduct quantitative experiments on piano cover generation and provide qualitative demos of style transfer. Results demonstrate improved audio-to-symbolic coherence and musicality, highlighting the potential of this framework for controllable, style-aware music generation beyond explicitly labeled content.

7 Ethics Statement

We confirm that our work adheres to the ICLR Code of Ethics. Datasets used in this study are open-source with appropriate licenses: the POP909 dataset under MIT license and the PIAST dataset under CC-BY-NC 4.0 license. Our subject evaluation was conducted through online crowdsourcing, which bears minimal risk. Participants were informed that participation was voluntary and that they could withdraw at any time without negative consequences. No personally identifiable information was collected. Further details of the subjective evaluation setup are described in Section 4.4.3.

8 Reproducibility Statement

We have made every effort to ensure the reproducibility of our results. Section 4 provides a detailed description of our experimental setup, including the datasets (Section 4.1) and model configurations (Section 4.2). Note that, due to copyright restrictions, the audio portion of POP909 is not publicly distributed. We obtained it by directly contacting the original authors. For objective experiments, we repeated each experiment 10 times and report the mean and standard error of the mean. For subjective evaluation, we applied within-subject ANOVA followed by post-hoc paired t-tests. To further facilitate reproducibility, we will release our implementation code upon publication.

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A Model Configuration and Training Details

We use MusicGen-Large (Copet et al., 2023) as our audio LM. We discard the text encoder and retain only the music decoder, a 48-layer Transformer. Audio codecs are fed to the decoder and we extract the hidden representations from the 25th layer, as prior probing studies (Wei et al., 2024; Ma et al., 2024; Vásquez et al., 2024; Castellon et al., 2021) suggest that middle layers capture more musically meaningful features. This setup retains 1.7B frozen parameters from MusicGen.

For symbolic music arrangement, we adopt MuseCoco-xLarge (Lu et al., 2023), which is a 24-layer Transformer decoder pre-trained on large-scale symbolic music corpora. We remove its text-related components and keep 1.2B frozen parameters from the music decoder.

The Q-Former comprises 186M learnable parameters, which is significantly smaller than the billion-scale backbone models. In Stage 1, it is pre-trained in FP16 using batch size 128 for 10 epochs (130K iteration). The LoRA adaptor in Stage 2 adds 5M parameters and we fine-tune the model for another 5 epochs using batch size 32. Both training stages are conducted on four RTX A40 GPUs (48GB each). We use the AdamW optimizer (Loshchilov & Hutter, 2019) with an initial learning rate of 1e-4, a linear warm-up over the first 1k steps, and a cosine decay schedule to a final rate of 1e-5. At test time, we use top-k sampling with $k = 15$.

B Limitation

Our proposed method demonstrates the ability to learn implicit music style from audio. At the current stage of this work, we acknowledge that the extracted style primarily represents global music characteristics. The finer, time-varying structures are not yet explicitly modeled. This limitation arises in part from our audio-to-symbolic formulation, which arranges a 4-bar piano performance globally conditioned on a 10-second audio reference. Although longer-range generation can be achieved by windowed sampling, it may still fail to capture the structured evolution of stylistic traits spanning multiple sections. Nevertheless, our framework represents a significant step forward in

improving audio-symbolic coherence, which lays a solid foundation for future advancements. Also, subject to the availability of audio-symbolic data, this work is dedicated to piano arrangement. The cross-modal arrangement of long-term, multi-track music would be a more challenging topic, which points to opportunities for future exploration.

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