Can Impressions of Music be Extracted from Thumbnail Images?

Takashi Harada
The University of Tokyo

Takehiro Motomitsu
Hokkaido University

Katsuhiko Hayashi
The University of Tokyo

Yusuke Sakai
NAIST

Hidetaka Kamigaito
NAIST

katsuhiko-hayashi@g.ecc.u-tokyo.ac.jp

Abstract

In recent years, there has been a notable increase in research on machine learning models for music retrieval and generation systems that are capable of taking natural language sentences as inputs. However, there is a scarcity of large-scale publicly available datasets, consisting of music data and their corresponding natural language descriptions known as music captions. In particular, non-musical information such as suitable situations for listening to a track and the emotions elicited upon listening is crucial for describing music. This type of information is underrepresented in existing music caption datasets due to the challenges associated with extracting it directly from music data. To address this issue, we propose a method for generating music caption data that incorporates non-musical aspects inferred from music thumbnail images, and validated the effectiveness of our approach through human evaluations. Additionally, we created a dataset with approximately 360,000 captions containing non-musical aspects. Leveraging this dataset, we trained a music retrieval model and demonstrated its effectiveness in music retrieval tasks through evaluation.

1 Introduction

The enjoyment of music is a highly personal experience, and the ways in which individuals find pleasure in it vary greatly. One method of enjoying music involves listening to tracks that best suit one's current mood or situations, such as during events like birthdays or in accordance with the season. Furthermore, individuals often find pleasure in music through discovering songs that match their preferred genres or instruments, and even in creating new music by utilizing the characteristics of existing music. As our interaction with music becomes more sophisticated, the development of music retrieval and generation systems that are customized to individual tastes and preferences is increasingly important.

	Musical aspects	**Non-musical aspects**
Perspective	- genre - instruments - tempo	- suitable situations - seasons, times of day - evoked emotions
Music caption	"Modern jazz played with a triumphal trumpet"	"Calm song ideal for listening on a night with a visible starry sky"

Table 1: Examples of musical and non-musical aspects.

In the domain of music retrieval, studies such as MusCALL (Manco et al., 2022a) have investigated the potential for efficient retrieval of music using natural language sentences as inputs, employing contrastive learning methodologies (Le-Khac et al., 2020). Efforts similar to those of MuLan (Huang et al., 2022) are currently being pursued in the field. In the realm of music generation, research initiatives such as MusicLM (Agostinelli et al., 2023), MUSICGEN (Copet et al., 2023), Mubert (Mubert-Inc, 2022), and Riffusion (Forsgren and Martiros, 2022) are integrating elements from systems like MuLan to produce high-quality music from textual descriptions. These music retrieval and generation models are dependent on natural language descriptive texts, commonly known as music captions, which contain information pertinent to music.

However, a notable challenge emerges, as the bulk of music caption data utilized in these models and systems is not accessible to the public, largely due to copyright constraints. Furthermore, because existing descriptive texts primarily focus on musical information, they hinder users without extensive musical knowledge from efficiently conducting music retrieval and generation that is based solely on musical elements. Consequently, there is an urgent need to develop and disseminate music caption data that includes a variety of elements, both musical and non-musical aspects, to the public.

To ensure the diversity of music caption data, it is imperative to include descriptions from two distinct perspectives: musical and non-musical aspects, as delineated in Table 1. The musical aspects encompass information like genre and tempo, which can be extracted from music data through music information processing, as exemplified by initiatives such as LP-MusicCaps (Doh et al., 2023) and others (Liu et al., 2023c; Manco et al., 2021). In contrast, non-musical aspects include individual impressions and emotional responses associated with music, encompassing elements such as suitable situations for listening to a track, associated seasons and times of day. The direct extraction of such information from music data poses significant challenges. Consequently, there is a notable deficiency in music caption data that includes non-musical aspect descriptions, and efforts toward their automatic generation are markedly limited.

To address this issue, we suggest focusing on the thumbnail images associated with music clips on platforms such as YouTube to extract information pertaining to non-musical aspects. Generally, thumbnail images significantly influence user engagement and click-through rates for content. In the context of music clips, thumbnail images serve as a succinct visual representation of the music's impression, enabling users to decide at a glance whether it aligns with their music preferences. In this research, we introduce a methodology for the automatic generation of music caption data, enriched with non-musical aspects derived from these thumbnail images. The validation results demonstrate that our proposed method is capable of accurately generating music captions that express non-musical aspect information, outperforming baseline methods. Furthermore, we have made public a dataset (`https://github.com/hu-kvl/llava_music_caption`) containing approximately 360,000 music captions developed using our approach. The utility of this dataset was also assessed within a music retrieval model, further substantiating its effectiveness. The details regarding the dataset creation and the evaluation of the music retrieval model are provided in the Appendices.

2 Related Work

To address the scarcity of music caption datasets, the LP-MusicCaps (LLM-Based Pseudo Music Captioning) initiatively utilized GPT-3.5 Turbo (OpenAI, 2022), a Large Language Model (LLM), for generating music captions across various tasks employing a comprehensive music tag dataset (Law et al., 2009; Bertin-Mahieux et al., 2011). The dataset produced, encompassing approximately 2.2 million captions and 500,000 audio clips paired with tags, has been made publicly available. It facilitates the automated generation of music captions with an enriched vocabulary while ensuring alignment with tags and grammatical precision. Notably, these methods utilize LLMs to focus on generating music captions that incorporate musical elements derived from tags, in contrast to our approach of enriching captions with non-musical aspects.

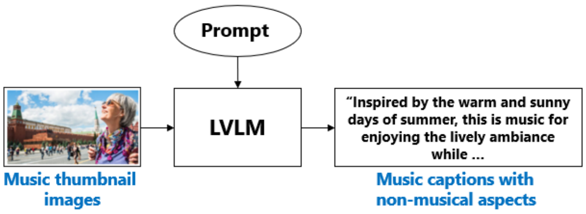

Prompt
LVLM
"Inspired by the warm and sunny days of summer, this is music for enjoying the lively ambiance while ...
Music thumbnail images
Music captions with non-musical aspects

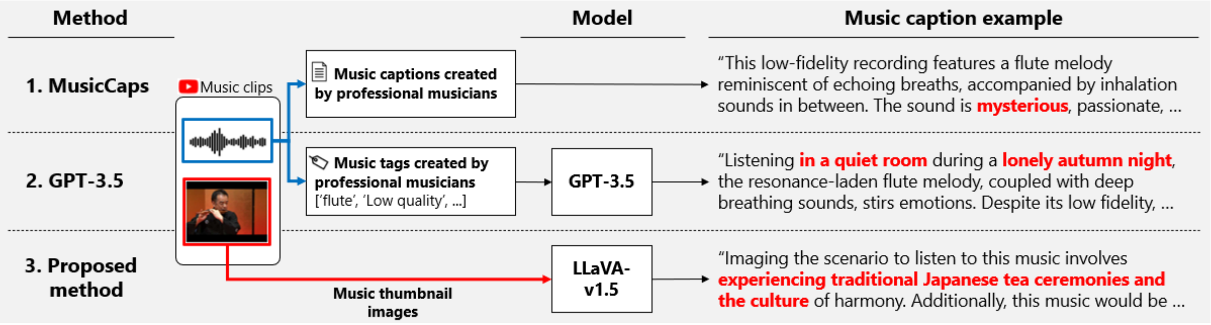
Figure 1: Overview of the music captioning method using thumbnail images.

While our study focuses on the automatic generation of music captions enriched with non-musical aspects using thumbnail images, there exists related research that leverages image intermediary representations for generating lyrics (Watanabe and Goto, 2023). This research tackles the challenge of assisting users in conveying appropriate messages and words in lyric creation.

Contrastive Language-Image Pre-training (CLIP) (Radford et al., 2021) uses a dual-encoder architecture to embed images and text into a shared latent space. CLIP has been influential in its demonstration of extracting highly generic visual representations from natural language, and MusCALL (Manco et al., 2022a) also adopts this dual-encoder contrastive learning approach pioneered by CLIP. MuLan (Huang et al., 2022) represents a similar endeavor in this field. Additionally, CLAP (Wu et al., 2023) is a model that applies CLIP's methodology to the audio domain. A cross-modal retrieval method between music and images has been also investigated in (Nakatsuka et al., 2023). In this study, we train a music retrieval model using pairs of music captions and music data created through the proposed method, and assess its effectiveness in music retrieval tasks where input queries are written in natural language sentences.

Evaluation Metric	Details of Evaluation Metric	Score
Positive	Assuming a music generation model that generates music from the provided text, this text contains and accurately expresses the corresponding non-musical aspects.	2
Neutral	Assuming a music generation model that generates music from the provided text, this text contains the corresponding non-musical aspects, but their expression is not accurate.	1
Negative	This text does not contain the corresponding non-musical aspects.	0

Table 2: Metrics for the human evaluation.



"This low-fidelity recording features a flute melody reminiscent of echoing breaths, accompanied by inhalation sounds in between. The sound is **mysterious**, passionate, ...

"Listening **in a quiet room** during a **lonely autumn night**, the resonance-laden flute melody, coupled with deep breathing sounds, stirs emotions. Despite its low fidelity, ...

"Imaging the scenario to listen to this music involves **experiencing traditional Japanese tea ceremonies and the culture** of harmony. Additionally, this music would be ...

Figure 2: Details of the proposed music captioning method and the methods used for comparison.

3 Proposed Method

This study is centered around thumbnail images linked to music clips on platforms like YouTube. Figure 1 provides an overview of our proposed methodology. In our approach, we first input the thumbnail image into a Large Vision-Language Model (LVLM), a large-scale language model capable of processing images. Following this, the LVLM, adapted using a meticulously crafted prompt, generates a music caption. This procedure facilitates the automatic generation of music captions that incorporate non-musical elements.

To ensure that the features of the thumbnail images are not included in the captions generated by the LVLM, we developed a strategic prompting method. Specifically, we guide the model to initially describe the features of the image itself, such as the content depicted in the thumbnail or its overall mood, in the initial segment of the generated text. In the subsequent part, we prompt the model to articulate non-musical aspects that are evoked by these features or the overall mood.

Moreover, by directing the LVLM to distinctly express the features of the thumbnail image in the first portion of the generated text, we successfully separate the description of thumbnail image features from the music caption generation. This not only achieves effective compartmentalization but also leverages techniques like the Chain of Thought (Wei et al., 2022), resulting in the production of high-quality music captions enriched with diverse non-musical elements.

4 Human Evaluation

4.1 Experimental Setup

For the generation of captions to be evaluated, we utilized the MusicCaps (Agostinelli et al., 2023) dataset[1]. MusicCaps primarily includes descriptions of music information from YouTube music clips, including corresponding music captions and music tags created by professional musicians. In our study, we selected 50 songs from MusicCaps, ensuring a balanced distribution across genres, for evaluation. For each song in the evaluation, three types of captions were prepared:

1. Manually created captions originally assigned to the dataset (MusicCaps).
2. Captions automatically generated using a LLM in accordance with the LP-MusicCaps (Doh et al., 2023) study approach, employing music tags (GPT-3.5).
3. Captions automatically generated from thumbnail images using the LVLM (Proposed method).

The distinct caption generation processes for each method are depicted in Figure 2. For GPT-3.5, we employed the GPT-3.5 Turbo language model, instructing it to describe non-musical aspects based on music tags and those tags them-

[1] https://huggingface.co/datasets/google/MusicCaps

	MusicCaps	GPT-3.5	**Proposed Method**
Situation	39.0	46.5	**75.5**
Time/Season	6.0	35.0	**72.0**
Emotion	36.5	**89.0**	83.0
Total	81.5	170.5	**230.5**
All 2s count	1.5	13.0	**23.5**

Table 3: Human evaluation scores and the count of All 2s.

selves. For the proposed method, we selected the open-source LLaVA-v1.5 (Liu et al., 2023b,a)[2] as the LVLM and tuned the prompt to align with our proposed method. The average lengths of the captions were 148.7 characters for MusicCaps, 146.0 characters for GPT-3.5, and 135.8 characters for the proposed method.

To evaluate each set of captions, a human evaluation was conducted. For the proposed method, only sections of the generated results related to non-musical aspects, located in the latter part of the output, were extracted for evaluation.

4.2 Evaluation Procedure and Metrics

For the human evaluation component, we enlisted two adult Japanese male speakers as evaluators. These evaluators listened to each music clip for approximately one minute before reviewing the three captions generated by each method. They then rendered absolute evaluations using a three-point scale (positive, neutral, negative) based on three perspectives (we referred to (Manco et al., 2022b)): suitable situations for listening to the track (Situation), associated times of day or seasons (Time/Season), and the emotions evoked as a result of listening (Emotion), as delineated in Table 2. To circumvent order bias, the captions were presented in a randomized sequence.

To facilitate the aggregation of results, the evaluators' three-tier assessments were converted into scores, as illustrated in Table 2. The final results reflect the average scores across evaluators, providing a cumulative score for the full dataset of 50 entries for each perspective. Furthermore, the aggregate values for each perspective and the average count of tracks where all three perspectives achieved a perfect score, designated as the "All 2s count," are also reported. It is predicated on the premise that captions with higher scores and greater counts not only contain non-musical aspects but also exhibit expressiveness.

4.3 Results and Discussion

The evaluation results are presented in Table 3, and actual music caption examples are shown in Figure 2, using the case of MusicCaps with "YouTube Video ID (ytID):0u5-WiBKam8" as an illustration.

Focusing on the aggregate scores across three perspectives, our proposed method achieved the highest evaluation outcomes. When compared to GPT-3.5, our method surpassed it by a total of 60 points in aggregate scores. Based on this result, it can be inferred that music captions, including non-musical aspects, can potentially be generated using information extracted from thumbnail images alone, without relying on musical or non-musical tag information created by professional musicians. Moreover, in every perspective, the scores of both our method and GPT-3.5 exceeded those of manually created captions by humans, MusicCaps. This suggests that when evaluating music captions based on three perspectives, LVLMs and LLMs can potentially be used to efficiently generate music captions that include non-musical aspects.

Finally, with a focus on the actual music caption examples, Figure 2 displays instances where non-musical aspects are expressed, written in red letters. Captions generated by our method are detailed and expressive, providing a rich representation of non-musical aspects. In contrast, captions by MusicCaps and GPT-3.5 include fewer descriptions of non-musical aspects and are more abstract.

5 Conclusion

In this study, we examined the importance of non-musical aspects, such as suitable situations for listening, times of day or seasons, and emotions evoked by listening. Specifically, we addressed the issue of the shortage of music caption data that includes non-musical aspect information, which is essential for constructing music retrieval and generation models. To address this issue, we proposed a method for generating music captions by leveraging thumbnail images. The effectiveness of the proposed method was validated through human evaluations. It has been reported that using the latest LVLMs to generate descriptions related to artworks has been successful (Hayashi et al., 2024; Saito et al., 2024; Ozaki et al., 2024), and we plan to update our experiments in accordance with the further advancements of LVLMs.

[2] We performed 4-bit inference on LLaVA-v1.5 13B.

References

Andrea Agostinelli, Timo I. Denk, Zalán Borsos, Jesse Engel, Mauro Verzetti, Antoine Caillon, Qingqing Huang, Aren Jansen, Adam Roberts, Marco Tagliasacchi, Matt Sharifi, Neil Zeghidour, and Christian Frank. 2023. MusicLM: Generating music from text. arXiv:2301.11325. *Preprint*, arXiv:2301.11325.

Thierry Bertin-Mahieux, Daniel Ellis, Brian Whitman, and Paul Lamere. 2011. The million song dataset. In *Proceedings of the 12th International Conference on Music Information Retrieval (ISMIR 2011)*, pages 591–596.

Jade Copet, Felix Kreuk, Itai Gat, Tal Remez, David Kant, Gabriel Synnaeve, Yossi Adi, and Alexandre Défossez. 2023. Simple and controllable music generation. arXiv:2306.05284. *Preprint*, arXiv:2306.05284.

Michaël Defferrard, Kirell Benzi, Pierre Vandergheynst, and Xavier Bresson. 2017. Fma: A dataset for music analysis. arXiv:1612.01840. *Preprint*, arXiv:1612.01840.

SeungHeon Doh, Keunwoo Choi, Jongpil Lee, and Juhan Nam. 2023. LP-MusicCaps: LLM-based pseudo music captioning. arXiv:2307.16372. *Preprint*, arXiv:2307.16372.

S. Forsgren and H Martiros. 2022. Riffusion. `https://riffusion.com/about`. Accessed: January 16, 2024.

Masataka Goto, Hiroki Hashiguchi, Takuichi Nishimura, and Ryuichi Oka. 2003. Rwc music database: Music genre database and musical instrument sound database.

Kazuki Hayashi, Yusuke Sakai, Hidetaka Kamigaito, Katsuhiko Hayashi, and Taro Watanabe. 2024. Towards artwork explanation in large-scale vision language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 705–729, Bangkok, Thailand. Association for Computational Linguistics.

Kun He, Yan Wang, and John Hopcroft. 2016. A powerful generative model using random weights for the deep image representation. arXiv:1606.04801. *Preprint*, arXiv:1606.04801.

Qingqing Huang, Aren Jansen, Joonseok Lee, Ravi Ganti, Judith Yue Li, and Daniel P. W. Ellis. 2022. MuLan: A joint embedding of music audio and natural language. arXiv:2208.12415. *Preprint*, arXiv:2208.12415.

Edith Law, Kris West, Michael I. Mandel, Mert Bay, and J. S. Downie. 2009. Evaluation of algorithms using games: The case of music tagging. In *International Society for Music Information Retrieval Conference*.

Phuc H Le-Khac, Graham Healy, and Alan F Smeaton. 2020. Contrastive representation learning: A framework and review. *Ieee Access*, 8:193907–193934.

Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. 2023a. Improved baselines with visual instruction tuning. arXiv:2310.03744. *Preprint*, arXiv:2310.03744.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. 2023b. Visual instruction tuning. arXiv:2304.08485. *Preprint*, arXiv:2304.08485.

Shansong Liu, Atin Sakkeer Hussain, Chenshuo Sun, and Ying Shan. 2023c. Music understanding LLaMA: Advancing text-to-music generation with question answering and captioning. arXiv:2308.11276. *Preprint*, arXiv:2308.11276.

Ilaria Manco, Emmanouil Benetos, Elio Quinton, and György Fazekas. 2021. MusCaps: Generating captions for music audio. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE.

Ilaria Manco, Emmanouil Benetos, Elio Quinton, and György Fazekas. 2022a. Contrastive audio-language learning for music. arXiv:2208.12208. *Preprint*, arXiv:2208.12208.

Ilaria Manco, Benno Weck, Philip Tovstogan, Minz Won, and Dmitry Bogdanov. 2022b. Song describer: a platform for collecting textual descriptions of music recordings. In *Extended Abstracts for the Late-Breaking Demo Session of the 23rd Int. Society for Music Information Retrieval Conf*, Bengaluru, India.

Mubert-Inc. 2022. Mubert. `https://mubert.com,https://github.com/MubertAI/Mubert-Text-to-Music`. Accessed: January 16, 2024.

Takayuki Nakatsuka, Masahiro Hamasaki, and Masataka Goto. 2023. Content-based music-image retrieval using self-and cross-modal feature embedding memory. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 2174–2184.

OpenAI. 2022. `https://openai.com/chatgpt`. Accessed: November 26, 2023.

Shintaro Ozaki, Kazuki Hayashi, Yusuke Sakai, Hidetaka Kamigaito, Katsuhiko Hayashi, and Taro Watanabe. 2024. Towards cross-lingual explanation of artwork in large-scale vision language models. *arXiv preprint arXiv:2409.01584*.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Shigeki Saito, Kazuki Hayashi, Yusuke Ide, Yusuke Sakai, Kazuma Onishi, Toma Suzuki, Seiji Gobara, Hidetaka Kamigaito, Katsuhiko Hayashi, and Taro Watanabe. 2024. Evaluating image review ability of vision language models. *arXiv preprint arXiv:2402.12121*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.

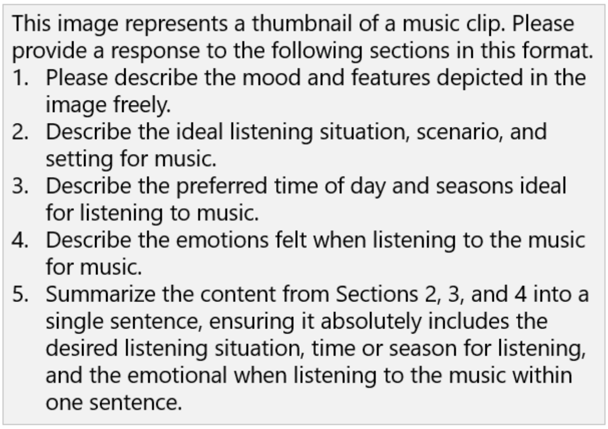
Kento Watanabe and Masataka Goto. 2023. Text-to-lyrics generation with image-based semantics and reduced risk of plagiarism. In *Ismir 2023 Hybrid Conference*.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837.

Yusong Wu, Ke Chen, Tianyu Zhang, Yuchen Hui, Taylor Berg-Kirkpatrick, and Shlomo Dubnov. 2023. Large-scale contrastive language-audio pretraining with feature fusion and keyword-to-caption augmentation. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE.

Genre	Train	Test (All 2s)	Total
house	49,942	80 (49)	50,022
edm	41,406	80 (53)	41,486
classic	32,695	80 (55)	32,775
chill	31,888	80 (62)	31,968
lofi	27,084	80 (62)	27,164
nightcore	24,717	80 (46)	24,797
anime	24,664	80 (55)	24,744
pop	24,658	80 (53)	24,738
rock	24,425	80 (37)	24,505
instrumental	23,483	80 (59)	23,563
tropical house	21,655	80 (56)	21,735
jazz	12,676	80 (51)	12,756
r&b	8,258	80 (60)	8,338
hiphop	7,812	80 (49)	7,892
bigroom	5,542	80 (43)	5,622
Total	360,905	1,200 (790)	362,105

Table 4: Number of data samples by genre.



This image represents a thumbnail of a music clip. Please provide a response to the following sections in this format.

1. Please describe the mood and features depicted in the image freely.
2. Describe the ideal listening situation, scenario, and setting for music.
3. Describe the preferred time of day and seasons ideal for listening to music.
4. Describe the emotions felt when listening to the music for music.
5. Summarize the content from Sections 2, 3, and 4 into a single sentence, ensuring it absolutely includes the desired listening situation, time or season for listening, and the emotional when listening to the music within one sentence.

Figure 3: Prompt 1: prompt to generate music captions from thumbnail images.

A Appendices

A.1 Open Music Caption Dataset

In this research, we employed the proposed method to create an open music caption dataset comprising approximately 360,000 pairs of music clips and their associated non-musical aspect captions. For this dataset, 15 music genres were selected based on their common usage in music databases (Goto et al., 2003), datasets (Defferrard et al., 2017), and streaming services. Table 4 provides a detailed breakdown of each genre along with the corresponding number of data entries. The music clips used were sourced by searching for the respective genre names and using the tracks found in playlists, with no intentional filtering applied. However, some clips that could not be acquired due to reasons such as privacy or age restrictions were excluded.

The construction of the training dataset entailed utilizing the proposed method to input thumbnail images of YouTube music clips and Prompt1 (see Figure 3) into the LLaVA model. Prompt1 is designed to facilitate the generation of content across five sections, encompassing the description of the mood and features of the thumbnail image, the preferred listening situation, scenario, and setting, the ideal times of day and seasons for listening, the emotions experienced while listening to the music, and a summarizing sentence that encapsulates the aspects detailed in sections 2, 3, and 4. The structured prompts were devised to distinctly separate the description of image features from the caption generation process, thereby enhancing the efficacy of the Chain of Thought approach.

The resulting training dataset includes fields such as “YouTubeID,” “URL,” “Genre,” “Caption,” and “Sentence” for each music clip. The “Sentence” field contains the entire content of Prompt1, enabling its potential use as a comprehensive, non-musical aspect-inclusive music caption.

A.2 Evaluation Dataset

For the creation of the evaluation dataset, our objective was to generate ground truth data that aligns with human perceptions and sensitivities towards music. From the training dataset, we randomly selected 80 music clips for each of the 15 genres, resulting in a total of 1,200 clips for evaluation. These clips were assessed by a musically knowledgeable adult using a three-point scale based on the perspectives detailed in Section 4, following approximately a minute of listening to each clip. The evaluated aspects included the ideal listening situation, the most suitable times of day or seasons for listening, and the emotions experienced during listening.

The evaluation dataset comprises fields such as "YouTubeID," "URL," "Genre," and "Caption," as well as "Situation," "Time/Season," and "Emotion" for each music clip. The latter three fields encapsulate the scores obtained from the human evaluations, corresponding to the three outlined perspectives. It is crucial to note that both the training and evaluation datasets are entirely in English. Table 4 details the breakdown and data count for each genre, including the number of music clips that received a "All 2s."

A.3 Validation with music retrieval Model

To evaluate the appropriateness of the newly created dataset for general user retrieval, we conducted an assessment by training a music retrieval model on the music caption dataset. The efficacy of the model is gauged based on its proficiency in accurately retrieving relevant items from the dataset.

A.3.1 Experimental Setup

To validate the effectiveness of the created dataset, we utilized the MusCALL music retrieval model (Manco et al., 2022a). MusCALL is a cross-modal contrastive learning model that facilitates both text-based music retrieval and music-based natural language retrieval. The architecture of the model includes a Transformer (Vaswani et al., 2017; Radford et al., 2019) for text encoding and a ResNet-50 (He et al., 2016), equipped to handle audio input, for audio encoding. The embeddings generated by these encoders are utilized to calculate cross-entropy loss, aimed at minimizing the cumulative losses of text and audio embeddings. The model's configurations, such as hyperparameters, are aligned with those established in MusCALL.

Genre	R@1↑	R@5↑	R@10↑	MedR↓
house	12.2	38.8	**59.2**	**8**
anime	5.5	27.3	**56.4**	**9**
instrumental	16.9	37.3	**57.6**	**9**
jazz	7.8	35.3	51.0	10
classic	10.9	36.4	50.9	10
pop	5.7	20.8	47.2	11
rock	10.8	35.1	46.0	11
chill	6.5	24.2	37.1	14
nightcore	2.2	19.6	37.0	14
tropical house	10.7	23.2	41.1	14
hip hop	2.0	28.6	42.9	15
big room	0.0	9.3	25.6	17
edm	7.5	17.0	32.1	17
lofi	12.9	30.6	38.7	17
r&b	3.3	20.0	28.3	23
Average	7.7	26.9	43.4	13.3

Table 5: Results of text to audio cross-modal retrieval task.

A.3.2 Dataset

For the training and evaluation of the MusCALL model, three distinct datasets - train, validation, and test - are employed. To construct the validation dataset, we randomly selected 30,000 entries from the training data, as delineated in Section A.1. Furthermore, 790 entries that are all categorized as "All 2s" from the 1,200 human-evaluated music clips were utilized as the test dataset. A detailed breakdown of the data utilization is provided in Table 4.

It is crucial to emphasize that the audio data used for this validation consists of 30-second clips extracted from YouTube music clips. These clips are accompanied by captions that are derived from the non-musical aspects indicated in the dataset's "Caption" column.

A.3.3 Evaluation Metrics

This experiment fundamentally represents a cross-modal retrieval task, tasked with evaluating the model's proficiency in retrieving items across different modalities. To assess the model's retrieval accuracy, we employ standard cross-modal retrieval metrics, namely Recall at K (R@K) and Median Rank (MedR). Specifically, we set K = {1, 5, 10}, which entails measuring the percentage of queries where the correct pair is ranked within the top k and the median rank of the correct pair, respectively, across various genres.

A.3.4 Results and Discussion

The outcome of the cross-modal retrieval tasks, namely retrieving music from text, is delineated in Table 5 for each genre. In genres such as house,

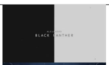
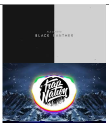
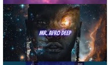
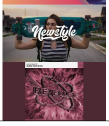
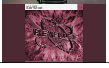
Ranking	YouTubeID	Thumbnail	Title	Evaluation
1	POHHAe0eTfA		ALEJANDRO - Black Panther	Good
2	W3H_8l6dvZs		Crypto - Faded (feat. Constance)	Fair
3	kFDfvMr1Pd4		JOXION - 094 [Arcade Release]	Excellent
4	N4Up97ZOv0g		Sora - Changes	Good
5	LL1owMMYP78		Black Gypsies - Kira (Original Mix)	Poor
6	AWXsZYhlmwg		Free My Body	Excellent
7	8xn5gH3XUkQ		New Blood & RCOP - Murda Sound	Good
8	JY97C7EztAg		S'hustryi Beats - Anti-Covid19	Poor
9	q3ugvrgOri4		Close Your Eyes (Extended Mix)	Good

Table 6: Retrieval results and evaluations for the query "Energetic songs for a late-night drive."

anime, instrumental, jazz, classic, pop, and rock, the model displays high accuracy in pinpointing relevant pairs, as reflected by the R@10 and MedR metrics in Table 5. This underlines the dataset's efficacy for these genres.

Conversely, in genres like big room, hip hop, and R&B, the model shows diminished retrieval performance, notably in terms of R@1. An examination of the dataset distribution (Table 4) indicates a significant scarcity of data entries in these genres compared to others. This paucity of data is identified as a key contributor to the reduced retrieval performance. Therefore, it is imperative to enrich the dataset for genres with limited entries to improve the model's retrieval proficiency in those specific areas.

A.3.5 Evaluation as Music Retrieval System

In this section, we conduct a more pragmatic evaluation of the experiments. Our aim is to validate the effectiveness of the dataset developed in this study for constructing a music retrieval system that incorporates non-musical aspects in retrieval queries.

Applying the ranking methodology utilized in the cross-modal retrieval task, we implemented a retrieval system that is capable of retrieving music from text queries. This retrieval was executed across all 790 music clips from various genres in the evaluation dataset, each with All 2s. A text query was employed: "Energetic songs for a late-night drive." The top 9 results for the query were presented, accompanied by the author's subjective evaluations of the music clips, categorized as "Excellent," "Good," "Fair," or "Poor."

The findings are exhibited in Table 6. Listening to the music clips retrieved for "Energetic songs for a late-night drive," the top result resonates with the energetic and intense vibe suitable for a nighttime drive. This outcome indicates the dataset's capability in supporting a music retrieval system based on non-musical aspects.

Furthermore, despite the lack of explicit musical aspect information in both queries, the retrieval system successfully retrieved relevant music. This implies that the system can cater to users without specific music-related expertise, enabling music retrieval based on impressions and emotional cues, thereby enhancing the diversity and flexibility of music retrieval.

Therefore, the retrieval system evaluated in this analysis demonstrates its proficiency in retrieving music appropriate for non-musical aspect descriptions in natural language queries. The results underscore the efficacy of the dataset created in this study for developing a comprehensive music retrieval system.