

MMtrail: A Multimodal Trailer Video Dataset with Language and Music Descriptions

Xiaowei Chi^{1*}, Yatian Wang^{1*}, Aosong Cheng^{2*}, Pengjun Fang^{1*}, Zeyue Tian^{1*}, Yingqing He¹, Zhaoyang Liu¹, Xingqun Qi¹, Jiahao Pan¹, Rongyu Zhang², Mengfei Li¹, Ruibin Yuan¹, Yanbing Jiang¹, Wei Xue¹, Wenhan Luo¹, Qifeng Chen¹, Shanghang Zhang^{2✉}, Qifeng Liu^{1✉}, Yike Guo¹

¹ The Hong Kong University of Science and Technology

² Peking University

Abstract

Massive multi-modality datasets play a significant role in facilitating the success of large video-language models. However, current video-language datasets primarily provide text descriptions for visual frames, considering audio to be weakly related information. They usually overlook exploring the potential of inherent audio-visual correlation, leading to monotonous annotation within each modality instead of comprehensive and precise descriptions. Such ignorance results in the difficulty of multiple cross-modality studies. To fulfill this gap, we present MMTrail, a large-scale multi-modality video-language dataset incorporating more than 20M trailer clips with visual captions, and 2M high-quality clips with multimodal captions. Trailers preview full-length video works and integrate context, visual frames, and background music. In particular, the trailer has two main advantages: (1) the topics are diverse, and the content characters are of various types, *e.g.*, film, news, and gaming. (2) the corresponding background music is custom-designed, making it more coherent with the visual context. Upon these insights, we propose a systemic captioning framework, achieving various modality annotations with more than 27.1k hours of trailer videos. Here, to ensure the caption retains music perspective while preserving the authority of visual context, we leverage the advanced LLM to merge all annotations adaptively. In this fashion, our MMtrail dataset potentially paves the path for fine-grained large multimodal-language model training. In experiments, we provide evaluation metrics and benchmark results on our dataset, demonstrating the high quality of our annotation and its effectiveness for model training.

1 Introduction

AI-driven movies and shot video production have a wide range of applications in people’s daily lives. Clearly, creating vivid videos requires more than just visual frame generation or individual modality-based ones. Thanks to various large-scale video-language datasets, numerous generative multimodal large language models have been developed to achieve this goal [4, 37, 6, 17, 31, 25, 53, 19]. However, the existing video-language datasets [9, 39, 56] typically focus on visual-based text descriptions, and they overlook the significance of the inherent visual-audio dependencies. It presents a complex challenge that demands cohesive integration of multiple modalities, yet remains largely unexplored.

*These authors contributed equally to this work.

✉ Corresponding authors.

[‡]Github repository:<https://github.com/litwellchi/MMTrail>

[§]Project Page:<https://mattie-e.github.io/MMTrail/>

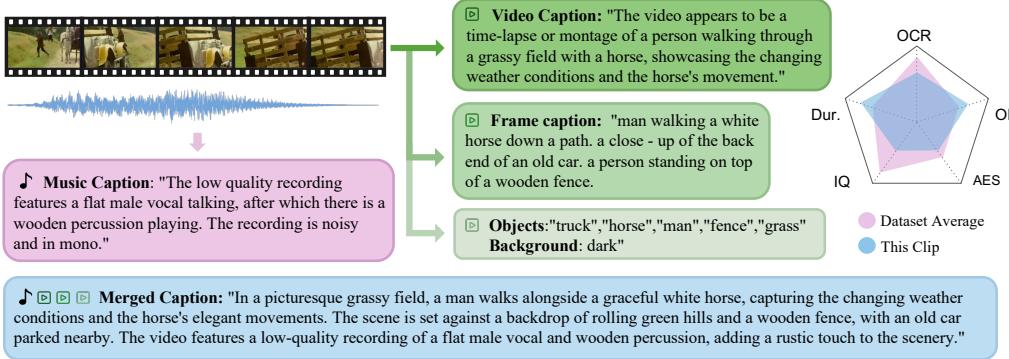


Figure 1: We present a video-language dataset with music captions, **MMTrail**.

Collecting high-quality multi-modality source data that preserves consistency between different modalities is challenging. Unlike previous datasets that only provide visual frame-based caption [1], multimodal datasets contain complex data formats (*e.g.*, music), resulting in more labor-intensive and time-consuming costs in data processing and annotation. Moreover, achieving a high correlation between audio and visual content presents challenges.

Targeting to fill the dataset gap by creating a comprehensive and accurate multi-modality visual-audio dataset, we first notice trailers. As a precursor to a full-length work, the video trailer has emerged as a vital tool for artists to showcase and disseminate their creations. These short videos typically combine the most compelling visual shots with carefully selected music, have high cross-modality consistency, and hold significant potential in broader multimodal research. The topics are diverse, and the content characters are of various types, *e.g.*, film, comedy, and gaming, as shown in Fig. 2. Significantly, the trailer format represents a unique, high-quality, video-centric multimodal data source that benefits further multi-modality research exploration and analysis.

In this work, we propose **MMTrail**, which aims to unlock the potential of multimodal content understanding and generation for innovative applications in video content generation. We first recognize the immense value of trailers as a video-centric dataset, especially considering the music alongside the videos. **MMTrail** contains 20M+ video clips from 290k trailer videos encompassing various source categories as shown in Fig. 2. To ensure the quality of our dataset, we have carefully designed a robust data filtering and cleaning methodology. We also provide extensive statistics works to demonstrate the diversity and complexity of our dataset.

To address the multimodal to language annotation challenge, we have designed a multimodal captioning pipeline incorporating diverse state-of-the-art (SOTA) captioning models [12, 64, 35]. Furthermore, we propose a language model fusion strategy to generate fine-grained multimodal captions. We have performed small-scale annotations on the entire dataset, created a multimodal annotation subset of 3 million samples **MMTrail-2M**, and provided a testing set **MMTrail-Test** with manually-adjusted multimodal caption.

We present evaluation metrics and benchmark results on our dataset, demonstrating the high quality of our annotations and their effectiveness for model training. Through extensive experiments and benchmarking, we showcase the difficulty and diversity of our dataset using various evaluation metrics. We also conduct human evaluations to validate the quality of our multimodal captioning

Table 1: Comparison of MMTrail-X and other Video to language datasets. MMTrail-X contains three sets(20M,2M, test) with 720p resolution.

Dataset	Year	Size	Caption	Modality	Clips	E(V)	E(T)	Resolution
WebVid [1]	2021	52khr	Alt-text	Video	10M	10s	-	360p
Panda [9]	2024	167khr	Auto	Video	70M	8.5s	13.2	720p
HD-VILA [61]	2022	371.5khr	ASR	Video	100M	3.6s	32.5	720p
MSR-VTT [60]	2016	40hr	Manual	Video	10K	15s	9.3	240p
InternVid [56]	2023	760.3khr	Auto	MM	100M	11.7s	11.6	720p
HowTo100M [39]	2023	134.5khr	ASR	MM	136M	3.6s	4	720p
MMTrail-20M	2024	27.1khr	Auto	Video	20M	4.6s	10.7	720p
MMTrail-2M	2024	8.2khr	Auto	MM	2M	13.8s	39.4	720p
MMTrail-Test	2024	3.2hr	Manual	MM	1k	11.6s	98.2	720p

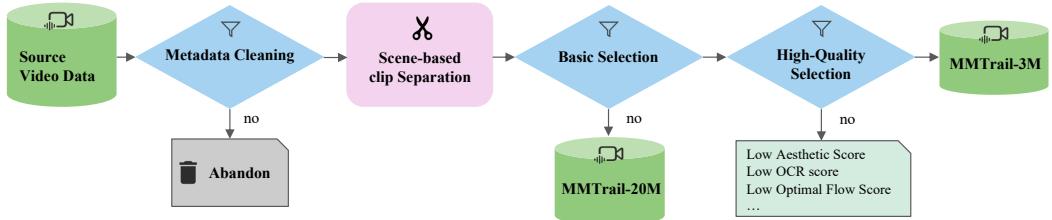


Figure 3: Data collection and cleaning pipeline of the MMTrail. Starting from the source video data, we follow the metadata cleaning, scene-cut, and basic filtering to obtain the full list of MMTrail-20M and High-Quality Selection to filter the MMTrail-2M.

pipeline. Furthermore, we fine-tune understanding models [66] and generative models [6] on a subset of our dataset, providing evidence of its high quality and efficacy. Additionally, we evaluate video understanding models on the MMTrail-Test, highlighting the challenges posed by our dataset, and evaluate video-music-based models to demonstrate the effectiveness of cross-modality tasks.

2 Related Work

2.1 Video generation and understanding

Video understanding and text-to-video generation are inherently connected tasks. In recent years, there has been remarkable progress in understanding models [57, 36, 69, 2, 63, 62, 33, 32, 58, 66, 8], which have greatly contributed to the advancement of text-based video generation techniques. The availability of large-scale datasets and diffusion models has revolutionized video generation, moving from pixel-level approaches like [21, 46, 20] to latent-level video diffusion models [18, 71, 5, 17]. Concurrently, understanding models have also witnessed significant improvements. A series of MLLM-based understanding models [35, 38, 47, 23, 23] has reached a satisfied understanding abilities. Besides, some surveys give detailed summaries of this area from different application areas or aspects [16]. The iterative interaction between video generation and understanding has led to the development of excellent large-scale datasets and models encompassing diverse approaches. Panda [9] introduced an auto-caption model distilled from video understanding models like VideoLlaMA [66], MiniGPT4 [72]. Furthermore, leading to a large amount of multimodal generation models [31, 59, 10, 28].

2.2 Video-Language datasets

Captioned video datasets are essential for text-to-video generation and understanding tasks. MSR-VTT [60], UCF-101 [48] are commonly used as evaluation sets. Anna et al. [42] presented 118,081 movie clips with descriptions. ActivityNet Caption [27] by Ranjay et al. is a benchmark involving event detection, natural language description, and event localization. WebVid [1], VideoFactory [54], and other works [44, 55, 49, 40], contain multilingual video descriptions, video clips, metadata such as titles, descriptions, tags, and channel names, and are used for tasks like video understanding,



Figure 4: Word cloud of the (left) objects and (right) background in MMTrail. Most of the objects are human, and most of the backgrounds are indoor scenes like office, kitchen, etc.

text-to-video retrieval, and audio-video captioning with weak annotations. Several datasets and approaches have utilized audio to enhance video captioning [39, 42, 65, 56, 9, 61]. These datasets consist of movies, web videos, YouTube videos, and high-resolution videos from popular YouTube categories, providing transcribed audio descriptions, narrations [39], ASR transcriptions [65], and multiple captions generated through a auto caption model [39, 9, 56].

However, existing works only use audio to enhance the video caption, using metadata or ASR to provide extra information for the video caption. A large-scale video-centric dataset that cooperates with high-quality music and multimodal caption is still lacking.

3 MMTrail-20M Dataset

To boost the performance of multimodal generation tasks, we construct a high-quality multimodal dataset based on trailers, which offers a wealth of multimodal information and diverse categories that distinguish them from existing large-scale video-language datasets.

3.1 Data Collection Pipeline

Trailers, as unique, well-made video types, have particular data distribution and exceptional quality. The trailer videos usually contain multiple themes, including movies, TV shows, games, etc. They are well organized with the most attractive clips of the corresponding videos. At the same time, most of them are accompanied by corresponding background voices and music. Such rich and high-density information is a complete challenge for the current Artificial Intelligence Generation Content(AIGC) task and brings considerable difficulties to data cleaning. To solve this challenging problem, we designed a comprehensive data collection and cleaning process as shown in Fig. 3 to deal with such complex videos, as described in this section.

Collection Strategies To enrich the diversity of our MMTrail, we first employ the keyword “trailer” to retrieve various in-the-wild trailer videos. Such general-purpose trailer videos encapsulate a wide range of artistic works and genres. Then, we tailor the keywords more specifically to explicitly collect trailer videos with divergent sources. Those keywords include “Movie Trailers”, “Video Game Trailers”, “TV Show Trailers”, “Documentary Trailers”, etc. Through these two methods, we collect 285,518 comprehensive trailer videos with a total duration of 94,911,802.8 seconds.

Trimming To facilitate the extraction of various video information in subsequent analyses, we cut the original videos into clips based on the scenes. As the most mature and practical tool currently available, PySceneDetect* offers robust functionalities for this purpose. Thus, we use ContentDetector of PySceneDetect to compare the difference in content between adjacent frames and then cut the videos according to the predetermined threshold of 30. We finally generated 21,588,792 clips with an average duration of 4.6 seconds.

Motion Filtering Evaluating motion quality is a crucial step in selecting high-quality video content. Motion vectors and optical flow are both mainstream motion quality evaluation methods. In our case, trailer videos often have rapid cuts and transitions between scenes, posing challenges for optical flow-based analysis. Other than optical flow, motion vectors are more robust to these quick changes,

*<https://github.com/Breakthrough/PySceneDetect>

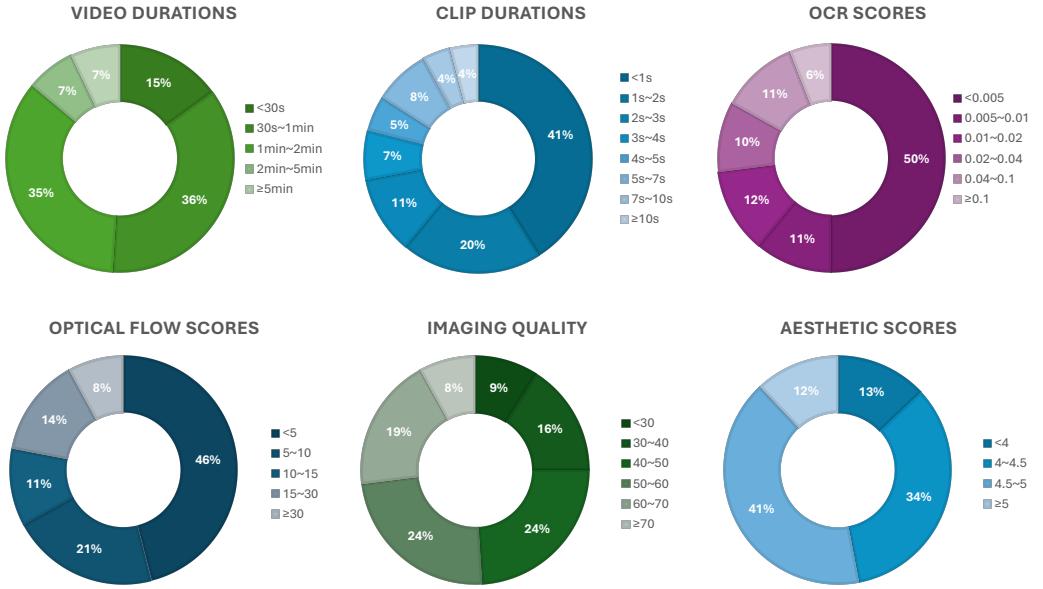


Figure 5: Statistic of the MMTrail clips. These evaluation scores collectively include OCR score, Video duration, optical flow score, clip duration, image quality, and aesthetic score, demonstrating the richness and diversity of MMTrail, making it a valuable resource for multimedia research.

as they rely on larger block units’ displacement rather than individual pixels’ continuous flow. On the other hand, motion vectors are more lightweight and can be calculated more efficiently. Thus, we leverage motion vectors to filter out clips with problems like static frames, title sequences, and slideshow-like playback.



Figure 6: Clips of high (left) and low (right) motion quality scores.

Diversity We evaluate the diversity and richness of our dataset from three aspects: theme, objects, and backgrounds. While collecting, we first assess the categories from the YouTube metadata provided by the video provider, as shown in Fig. 2. Furthermore, we generate an object-level caption list and background by Llava-Next [35] for a more accurate category-based generation. The word cloud of objects and backgrounds is shown in Fig. 4.

OCR Trailer videos often have text-heavy sections with high-quality text animations, like opening and ending credits. To identify these text-rich segments, we utilize OCR to detect the text content in the video frames and calculate the bounding box area of the text. This measurement reflects the amount of text in the clips.



Figure 7: Clips of high (left) and low (right) OCR scores.

Quality Statistics In addition to text detection, we considered image quality [22] and aesthetic scores [45] to enhance our analysis of trailer videos. These measures allowed us to evaluate frames’ visual fidelity, clarity, and aesthetic appeal, providing more comprehensive insights for trailer analysis and editing.



Figure 8: Clips of high (left) and low (right) image quality scores.

Audio Collection We extract the audio from video source segments with a sampling rate of 44.1 kHz. We use the PANNs [26] algorithm to perform music event detection, and over 70% of the audio segments contain music.

3.2 Video Captioning Pipeline

The MMTrail contains many complex themes, like subtitles and character animations, as shown in Fig. 2, which brings extraordinary complex work for video captioning. At the same time, smooth transition shots also make it impossible for traditional single-frame annotation methods to convey semantics coherently. Therefore, this section introduces a multi-temporal and multimodal caption pipeline containing a detailed video description from frame, motion, and music levels.

Frame Caption The auto-captioning pipeline has proven efficient in cutting-edge video generation foundation models. SVD [4] and Pandas [9] have given promising results and demonstrated the importance of high-quality frame captions for the generation model. We initially performed image-level captioning on the individual frames of the data. We employed coca [64] for each video clip to generate separate captions for three frames(first, middle, and last), resulting in relevant captions.

Clip Caption Having obtained concise captions for three frames that capture the essential information, we aimed to obtain fine-grained captions and variations between frames in the video. We concatenated multiple frames into a comic strip format and employed the LLaVA [35] image model to guide the description of the dynamic differences between frames. Additionally, leveraging a powerful multimodal language model, we incorporated OCR and more detailed summary descriptions to expand the information within the frame captions.

Categories and Background Noticing the LLM-based caption has hallucinations when describing the frame, we further generate word-level labels to enhance the annotation of the main objects and background. Initially, we utilized LLaVA’s QA capabilities to have the model answer questions about the background. Subsequently, through QA, we prompted the model to provide relevant category information. We conducted the word cloud in Fig. 4. and certified caption quality by subjective experience in Section 4.

Music Caption Moreover, given that trailer music usually has a well-designed audio effect and background music, we applied the music caption on our dataset rather than a standard audio caption. In our work, we used MusicCaps [12], an LLM-based music captioning model. The caption format is well designed with its description pipeline, which first describes its sound quality, a generated speech style, and a detailed description of its instrument and music style. More examples are shown in the Appendix. We further evaluate the generation tasks and the text-to-music generation based on the music caption, which shows the efficiency of our captioning and dataset.

OCR The trailer contains many text animations. Captioning the context inside the movie can also be a challenging task. In this task, we utilize the OCR ability by LlaVA [35] and caption the context for 5 frames of each video. We merge reliable text animation captions based on the previous method.

General caption Combining all the captions mentioned above, we use the language model llama2-13B [51] to merge all the captions and generate complete and high-quality multimodal captions. We evaluate the caption accuracy and quality by human preference in Section 4.

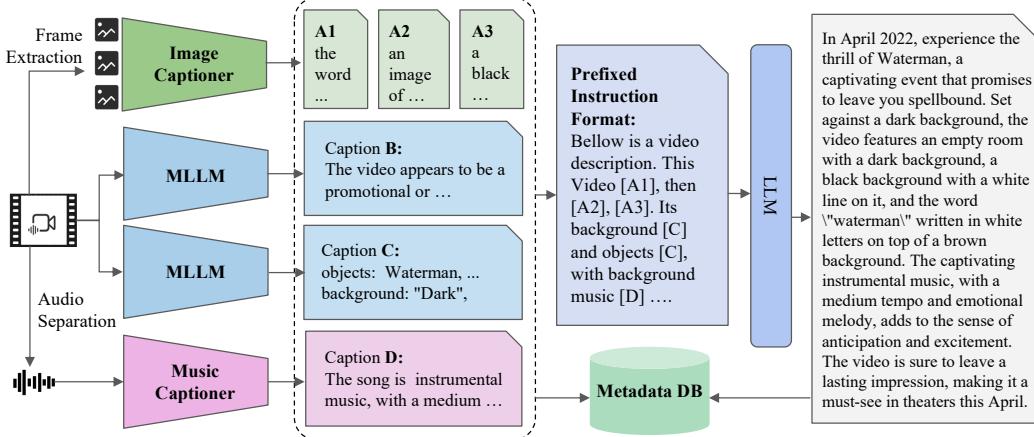


Figure 9: Data captioning pipeline. Starting from video clips, we extract frames and audio and then perform multiple rounds of captioning. A predefined instruction format combines multimodal captions, which serve as prompts for the language model and generate the final merged prompts.

Table 2: Comparison of MMTrail-2M and other Video-Audio Generation Dataset. For each dataset, we list the following information in each column: dataset name (Dataset), public year (Year), average duration per clip (Dur./Clip), total number of clips (#Clips), total number of hours (#Hours).

Dataset	Year	Dur./Clip	#Clips	#Hours
Audioset [15]	2017	10s	2M	5.8khr
VggSound [7]	2020	10s	210K	550hr
MMTrail-2M	2024	13.8s	2M	8.2khr
MMTrail-Test	2024	11.6s	1k	3.2hr

3.3 SubSet Separation

We applied the frame caption Section 3.2 for the full MMTrailer-20M video clips with 20M+ clips. We included the scale comparison with other large-scale datasets in Table 1, showing that our dataset is a large-scale video-language dataset. MMTrail has a resolution no smaller than 720p, and MMTrail-20M clips are 4.6s long on average.

High-quality Subset, named MMTrail-2M, contains a detailed multimodal caption. Compared to the original distribution, we sample MMTrail-2M to create a high-quality subset using the following criteria: 1. We filter out clips with motion scores below 0.45 or above 50. 2. We only retain the clips within the top 85% of image quality scores. 3. We only keep the clips within the top 85% of aesthetic scores. Furthermore, all clips in MMTrail-2M are longer than 4s and provided with all the captions, as shown in Fig. 9, including categories, background, frame captions, music captions, merged captions, etc. We also compare MMTrail-2M with Video-Audio datasets as shown in Table 2, MMTrail has a larger scale than existing datasets (Audioset [15] and VggSound [7]).

High-quality test set is extracted from the MMTrail-2M, we extract a fine-branded testing set that contains 1k video clips and multiple multimodal captions. Then, we manually adjust the merged caption to a manual caption to build a testing subset with trust-wise multimodal prompts. We test several tasks and models on the test set in Section 4 to show the complexity and difficulties of MMTrail. The test set has 98.2 words of caption on average and includes 3.2hr video clips.

4 Experiments

This section presents comprehensive experiments on multiple tasks to demonstrate our dataset's effectiveness, diversity, complexity, and difficulty.

4.1 Multimodal Captioning

We present the results of our human evaluation of video caption quality in Fig. 10. Ten videos were randomly selected from the MMTrail-Test dataset. They were rated on a scale of 0 to 10 based on

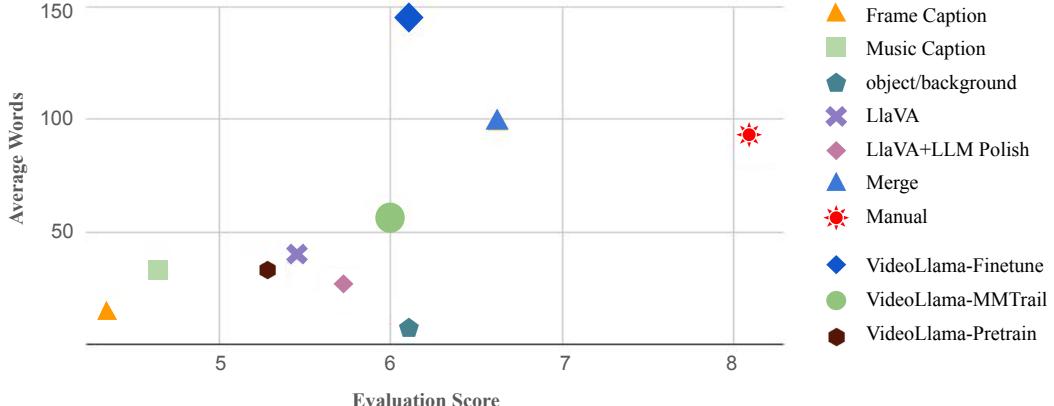


Figure 10: Human evaluation results of the captioning models on the MMTrail-Test. The X-axis is the average evaluation score from 0-10, and the Y-axis is the average word numbers.

Table 3: Comparison of VideoCrafter-2.0 and VideoCrafter-2.0(MMTrail) on 9 different dimensions. For every dimension, a higher score is better.

Dimensions(↑)	VideoCrafter-2.0	VideoCrafter-2.0(MMTrail)
temporal style	25.84	24.61
appearance style	25.13	24.10
image quality	67.22	69.78
dynamic degree	42.50	43.50
motion smoothness	97.73	98.33
temporal flickering	98.41	98.50
Subject consistency	96.85	98.62
background consistency	98.22	98.40
Overall consistency	28.23	25.33
Sum	64.45	64.57

general impressions, including aspects such as correctness, level of detail, richness, and fluency. The results of more than 100 sets of samples indicate that the manually adjusted prompts rating of 8.12 outperforms the auto-caption pipeline, while our merged captions achieve the second-best performance of 6.62. Despite being short and straightforward, object/background labels achieve a 6.02 evaluation score, demonstrating more correctness than other captions. Frame caption, music caption, and llaVA caption obtain 4.3, 4.6, and 5.4, respectively, and these findings demonstrate the effectiveness of our captions and highlight the quality of our labeled captions by human annotators.

4.2 Video Generation

The model was fine-tuned on the VideoCrafter-2.0 [37] dataset using 8 Tesla-H800 GPUs with a batch size of 3 for 10,000 steps at a learning rate of 6e-6. The training data was randomly sampled from the MMTrail-2M dataset, using the video captions as input. The evaluation results, shown in Table 3, include 9 matrices on the VBench [22], indicating that fine-tuning the model on the MMTrail-2M dataset led to improvements of 0.6 in motion smoothness and 1.77 in subject consistency, with a slight overall performance boost(0.12 higher) compared to the official VideoCrafter-2.0 checkpoint. Visual examples of the generated content are provided in Fig. 11, and additional demonstrations and experiment details will be included in the supplementary material. This thorough evaluation and comparison of the tuned model’s performance on critical metrics provides valuable insights into the effectiveness of the fine-tuning process and the potential benefits of leveraging the MMTrail-2M dataset for video generation tasks.

4.3 Video Understanding

Experiment Setting To evaluate the capability of our dataset in multimodal video understanding, we choose Video-LLaMA [66] as the baseline for the video captioning task. We use same model



Caption : A cute happy Corgi playing in park, sunset, watercolor painting.



Caption : A beetle emerging from the sand.

Figure 11: Two generation result of Videocrafter(MMTrail). The caption is from the VBench [22] evaluation prompts list; the given example shows the high quality in motion and object consistency.

Table 4: Comparison of Video-LlaMA model performance on the Trailer-Test dataset. The figure shows the results of three different versions of the Video-LlaMA model across five evaluation metrics, and the Video-LlaMA(MMTrail) version performs better on most evaluation indicators.

Model	BLEU-4↑	M↑	ROGUE-L↑	CIDEr↑	BERT↑
Video-LlaMA(Pretrain)	0.52	4.57	11.57	0.09	84.42
Video-LlaMA(Finetune)	3.94	14.05	22.67	2.45	85.48
Video-LlaMA(MMTrail)	5.59	13.83	24.97	24.79	87.21

and training config as Video-LlaMA, which use Vicuna-v0-7B as llama model [70], ViT [14] and Q-Former [67] as the video encoder and the linear projection layer from MiniGPT-4 [73]. We train 4 epochs by MMTrail-2M, each containing 2500 iters with batch size 32. We compare it with two official model weights: the pre-train Video-LlaMA weight on WebVid (2.5M video-caption pairs) and the fine-tuned Video-LlaMA.

Evaluation Metric We evaluate video understanding models on the MMTrail-Test. As for the evaluation metric, we choose the commonly used metrics in text generation tasks-BLEU-4 [41], ROGUE-L [30], METEOR [3], and CIDEr [52] to evaluate our result. All the metrics are computed using the pycocoevalcap [34] package. We also use BERTScore [68] to evaluate the contextual similarity for each token in the ground truth and the predicted captions. The results are reported in Table 4. The official weights show relatively low performance, highlighting the challenge of MMTrail, and the data distribution differs from their training data.

In addition, we also evaluated three checkpoints from Video-LlaMA [66] by human evaluation in Fig. 10 and found that the Video-LlaMA-MMTrail evaluation result slightly lags behind Video-LlaMA-Finetune but performs significantly better than Video-LlaMA-Pretrain. We provide further details in Section 4.3 for a more comprehensive understanding of our model.

4.4 Music Generation

We used text-to-music generation to evaluate the effectiveness of the video-music pair data and the labeled video caption and music caption. We use MusicGen [11] to generate music based on our video caption (VideoCap2Music) and music caption (MusicCap2Music). We use Kullback-Leibler Divergence (KL), Inception score (ISc), Frechet distance (FD), and Frechet Audio Distance (FAD) [24] to evaluate the generated music. Besides, we use the ImageBind-AV score (IB) to evaluate the audio-visual alignment between the video and the generated music. For the model with text input in Tab. 5, compared with video caption, the evaluation results on music caption are 0.13 better in KL, 0.65 in ISc, 3.64 in FD, and 1.21 in FAD, showing the domain gap of multimodal descriptions. This comparison shows that there is still a significant research gap between caption-music-video.

Table 5: Music generation evaluation results on the MMTrail-Test. We compare two types of captions and their 5 metrics. The results show that music caption performs better in music generation tasks.

Method	Input	KL↓	ISc↑	FD↓	FAD↓	IB↑
VideoCap2Music	Text	3.22	1.79	57.17	15.04	0.09
MusicCap2Music	Text	3.10	2.44	53.53	13.83	-

5 Conclusion

We introduce MMTrail, a comprehensive and accurate multi-modality visual-audio dataset to address the dataset gap. By utilizing the inherent value of trailers, which integrate visual, audio, and contextual elements, MMTrail offers detailed and precise multi-modality annotations. Our systematic captioning framework adaptively merges visual and musical perspectives, ensuring that the annotations capture the richness of multimodal content. Experimental results demonstrate the high quality of the MMTrail dataset, its effectiveness for fine-grained multimodal-language model training, and a variety of downstream applications. We believe this innovative dataset will unlock new possibilities in video content generation and significantly advance research in visual-audio understanding. The comprehensive and diverse nature of MMTrail makes it a valuable asset for the research community, paving the way for novel applications that leverage the power of multimodal learning.

A Captioning Pipeline

A.1 Music Caption

As trailer videos often contain a cacophony of audio tracks, which typically include background music and vocals, captioning audio poses a significant challenge. Therefore, to achieve optimal music captioning results, we initially utilize Demucs [43] for vocal separation on each audio clip. Subsequently, LP-MusicCap [13] is leveraged to caption the resultant audio, devoid of vocals, from the separation process.

A.2 Speech Recognition

Besides, the speech is also an important track of the trailer audio. Therefore, we further turn the speech into the text. Similar to our approach in music captioning, we use Demucs initially to perform vocal separation on each audio clip. Following this, Whisper is utilized to caption the separated vocal audio.

A.3 Merge Caption

B Captioning Pipeline

We use LLaMA-13B to merge the multiple captions, by constricting a pre-designed caption prompt as follows:

```
There are some descriptions of a video,
including video caption, music caption, background caption and the main
objects in the video.
Please combine all the descriptions into an overall description of the
video in only one paragraph.
Finally, please rewrite and polish it into an overall video description
in one paragraph and give me only the content of the video.
Background: {background}
Main objects: {objects}
Video caption 1: {image_cap}
Video caption 2: {frame_cap}
Music caption: {music_cap}
```

Music Caption for Unseparated Audio: This audio contains a male voice speaking in a lower key. Then a spoken word recording starts playing a melody on a marimba. This is an amateur recording. This may be playing in a tutorial video on the djembe.

Music Caption for Separated Audio: This audio contains someone playing a xylophone sound and rattles. This is an amateur recording. You can hear clicking and recording noises. T This audio contains a male voice speaking in a lower key. Then a spoken word recording starts playing a melody on a marimba. This is an amateur recording. This may be playing in a tutorial video on the djembe. his song may be playing demonstrating specific sounds on a device.

(a)

Music Caption for Unseparated Audio: The low quality recording features a flat male vocal talking, after which there is a synth pad speaking in the background. The recording is noisy and in mono.

Music Caption for Separated Audio: The low quality recording features a suspenseful synth pad played over playback that consists of loud bell tones and some sea waves sounds. The recording is noisy and in mono.

(b)

Music Caption for Unseparated Audio: The low quality recording features a flat female vocal talking over playback instrumental that consists of a flat male vocal talking, after which there is a harmonizing female vocal melody. The recording is noisy and in mono.

Music Caption for Separated Audio: This is the type of horn that would be heard in a distant battlecry. The clip features just this war horn, which sounds like the sound of a dog barking.

(c)

Music Caption for Unseparated Audio: This music is instrumental. The tempo is medium with a male voice speaking in an instructive manner. The music is like a tutorial on the guitar.

Music Caption for Separated Audio: This audio contains someone playing a marimba melody on a horn. This is an amateur recording. This may be playing in a church.

(d)

Figure 12: We provided an extra comparison of the music caption before and after the track separation. With our separation, the caption includes the description of the human voice as highlighted in red.

As illustrated in Figure 13, we use the LLaMA-13B to merge frame captions, lava captions, music captions, objects, and background into a final merge caption. By merging multiple captions, the merge caption offers a comprehensive and detailed description of the audiovisual content of videos. Its components mutually complement one another, ensuring that every aspect of the narrative receives attention and providing unique insights into various facets of the video content.

B.1 Frame Caption

We utilize LLava-v1.6-vicuna-7B as the image understanding model to generate captions for video clips. Initially, we filter out clips with durations of less than 1.0 seconds. Subsequently, we sample three frames at the fractions of 0.2, 0.5, and 0.8 of each clip’s total duration. The prompt is as follows:

Please describe the image in detail.

B.2 LLaVA Caption

We use the image understanding model LLaVA-13b [35] to caption each of our video clips. Specifically, for each clip, we sample frames at positions 0.1, 0.3, 0.5, 0.7, and 0.9, and then horizontally concatenate them into a single image, which serves as input for LLaVA-13b to generate captions. We construct the caption prompt as follows:

These are some keyframes of a video.

Please use one sentence to summarize the content of the video in detail.

```
Summarize the content of the entire video but not describe keyframes
frame by frame.
```

Moreover, we observe that the results of LLaVA captioning often contained some redundant information, as illustrated by the green sections in Figure 14. Therefore, we use LLaMA-13b to refine the LLaVA captions, eliminating much of the extraneous content and rendering the final captions more in line with human expression. We construct the prompt as follows:

```
[{caption}] This is a description of a video.
Please polish it to an overall video description in one sentence and
give me only the content of the video.
Do not use the words 'frame' and 'video'.
Describe the content of the video directly, which means do not start
with 'The video...' or something like that.
Do not add extra information that is not included in the original
description.
Here is an example: A dancer in a vibrant orange skirt and gray jacket
moves gracefully across the stage, her movements fluid and
expressive.
```

By combining frames and secondary polishing, we finally obtain high-quality captions that contain the main content information of the clips.

C Additional Experiments

C.1 Video Understanding Model

We use VideoLLaMA as our base model, which contains a llama model, a q-former, and a llama projection model. For LLM, we use llama vicuna-v0-7B. We also use model weight pretrained on minigpt4 to initialize our llama projection. In the training stage, we train from scratch and froze the Visual Transformer and LLM models. Only the visual q-former and the llama projection are trained in the pretraining stage. Following the video llama setting, we use a batch size of 32, and each video uniformly samples 8 frames with a 224 resolution. We train 5 epochs on our 2M training data. Each epoch contains 2500 iters with a linear warmup cosine lr. The weight decays are 0.05, and the warmup lr is 1e-6 with 2500 warmup steps, a 1e-4 init lr, and an 8e-5 minimum lr. The results can be seen in Table 6

Table 6: Comparison of Video-LLaMA model performance on the Trailer-Test dataset. The figure shows the results of three different versions of the Video-LLaMA model across five evaluation metrics, and the Video-LLaMA(MMTail) version performs better on most evaluation indicators.

Model	BLEU-4↑	M↑	ROGUE-L↑	CIDEr↑	BERT↑
Video-LLaMA(Pretrain)	0.52	4.57	11.57	0.09	84.42
Video-LLaMA(Finetune)	3.94	14.05	22.67	2.45	85.48
Video-LLaVA [29]	2.80	8.18	21.27	7.92	87.61
Video-LLaMA(MMTail)	5.59	13.83	24.97	24.79	87.21

C.2 Video to Music Generation

To further assess the effectiveness of the video-music pair data, we conduct an extended video-to-music generation task by training VidMuse [50] on an individual music subset of MMTail-2M. The results, shown in Table 7, demonstrate the high audio quality and strong audio-visual alignment between the video and the generated music achieved by our dataset.

Table 7: Video-to-music generation evaluation results on the MMTail-Test.

Method	Input	KL↓	ISc↑	FD↓	FAD↓	IB↑
VidMuse [50]	Video	0.988	1.231	48.144	5.078	0.183

D Dataset Details

Here is one metadata example of our dataset. We introduce the basic information of video and clips in the "basic" tag, including their duration, quality evaluation score, etc. The useful caption and description are saved in the "scene" tag.

```
{
  "basic": {
    "video_id": "-3r7ptf0bEs",
    "video_path": "group_33/-3r7ptf0bEs.mp4",
    "video_duration": 71.7333333333333,
    "video_resolution": [
      720,
      1280
    ],
    "video_fps": 30.0,
    "clip_id": "-3r7ptf0bEs_0000000",
    "clip_path": "video_dataset_33/-3r7ptf0bEs_0000000.mp4",
    "clip_duration": 7.03333333333333,
    "clip_start_end_idx": [
      0,
      211
    ],
    "image_quality": 36.83453941345215,
    "of_score": 12.92151,
    "aesthetic_score": [
      3.010026454925537,
      3.664743423461914,
      3.994750499725342
    ]
  },
  "camera": {
    "view_scale": "",
    "movement": "",
    "speed": ""
  },
  "misc": {
    "frame_caption": [
      "a person standing in a room with a laptop on their lap. ",
      "a black and blue background with the name of the series. ",
      "a black and white image of the words manga and comics. "
    ],
    "music_caption": [
      {
        "text": "This is an indie rock music piece. There is a male\nvocalist singing melodically in the lead. The main tune\nis being played by the electric guitar while the bass\nguitar is playing in the background. The rhythm is\nprovided by a simple acoustic drum beat. The atmosphere\nis easygoing. This piece could be used in the soundtrack\nof a teenage drama TV series as the opening theme.",
        "time": "0:00-10:00"
      }
    ]
  }
}
```

```
},
"scene": {
    "objects": [
        " Matheus Trindade",
        " de",
        " original",
        "Series",
        " Manga & Comics"
    ],
    "background": "Dark",
    "ocr_score": 0.07147466104497355,
    "caption": "The video is a series of original de Matheus Trindade comics, showcasing the artist's unique style and storytelling.",
    "polish_caption": "Original de Matheus Trindade comics showcase the artist's unique style and storytelling, featuring a series of vibrant and expressive illustrations that bring characters and scenes to life.",
    "merge_caption": "In this captivating video, Matheus Trindade's original comics come to life with vibrant and expressive illustrations, showcasing the artist's unique style and storytelling. Set against a dark background, the video features a series of dynamic and colorful images, including a person sitting in a room with a laptop, a black and blue background with the name of the series, and a black and white image of the words \"manga\" and \"comics.\\" The indie rock music piece, featuring a male vocalist and simple acoustic drum beat, adds an easygoing atmosphere to the video, making it perfect for the opening theme of a teenage drama TV series."
}
}
```

Frame Caption: "a man in a suit and tie sitting next to another man in a suit and tie.", "a man in a suit sitting in front of another man in a suit.", "a man in a suit and tie sitting at a table with another man."

LLaVA Caption: "A professional man in a suit listens intently to a standing colleague, who gestures with his hands as he speaks, in a serious and focused business environment."

Music Caption: "The low quality recording features a flat male vocal talking, after which there is a synth pad playing. It sounds like a tutorial and the recording is noisy and in mono."

Objects: " tie", "suit", "chair", "Man", "desk"

Background: "Office"

Merge Caption: "In a professional office setting, a well-dressed man in a suit and tie listens intently to his standing colleague, who passionately gestures with his hands as he speaks. The scene is set against a backdrop of sleek, modern furniture and a tidy desk, creating a focused and serious atmosphere. The video features a series of shots showcasing the men in suits engaging in a meeting or discussion, with one man sitting next to another, or sitting in front of each other at a table. The low-quality recording features a flat male vocal and a synth pad, giving the video a tutorial-like feel."

(a)

Frame Caption: "a woman sitting at a table with a glass of wine.", "a woman sitting at a table talking on a phone.", "a woman sitting at a table talking on the phone."

LLaVA Caption: "A woman sits at a table, surrounded by wine glasses, bottles, and a cake, engaging in conversation and interacting playfully with the objects on the table."

Music Caption: "This clip features a female voice speaking in an instructive manner. In the background you can hear birds chirping. This is an amateur recording."

Objects: "wine glass", "table", "kitchen", "Woman", "candle"

Background: "Kitchen"

Merge Caption: "In this video, a woman sits at a table in a cozy kitchen surrounded by wine glasses, bottles, and a cake, engaging in lively conversation and playfully interacting with the objects on the table. The scene is set against a peaceful background of birds chirping, adding to the warm and inviting atmosphere. The woman is shown speaking on the phone, laughing and smiling as she enjoys her wine and the company of those around her. The video features an amateur recording of a female voice speaking in an instructive manner, adding to the sense of intimacy and authenticity."

(b)

Frame Caption: "a man with long hair is looking at a mirror.", "a man with long black hair talking to a woman in front of a mirror.", "a man with long hair is looking at a woman."

LLaVA Caption: "A man with a beard expresses a range of emotions and reactions, from thoughtfulness to amusement, as he engages in a conversation or interview."

Music Caption: "The low quality recording features a tutorial that consists of a flat male vocal talking over sustained strings melody. It sounds like a tutorial and the recording is noisy and in mono."

Objects: " door", " room", " television", "Man", " beard"

Background: "Doorway"

Merge Caption: "The video, set against a doorway background, features a man with a beard engaging in a conversation or interview, expressing a range of emotions and reactions from thoughtfulness to amusement. He is surrounded by elements of a room, including a television, and is occasionally joined by a man with long hair who looks at a mirror or talks to a woman. The low-quality recording includes a tutorial with a flat male vocal over sustained strings melody, giving the video a noisy and mono feel."

(c)

Figure 13: We demonstrate more examples of the merged captions. As shown in the examples, all key information from different captions is merged together into a fluent paragraph.

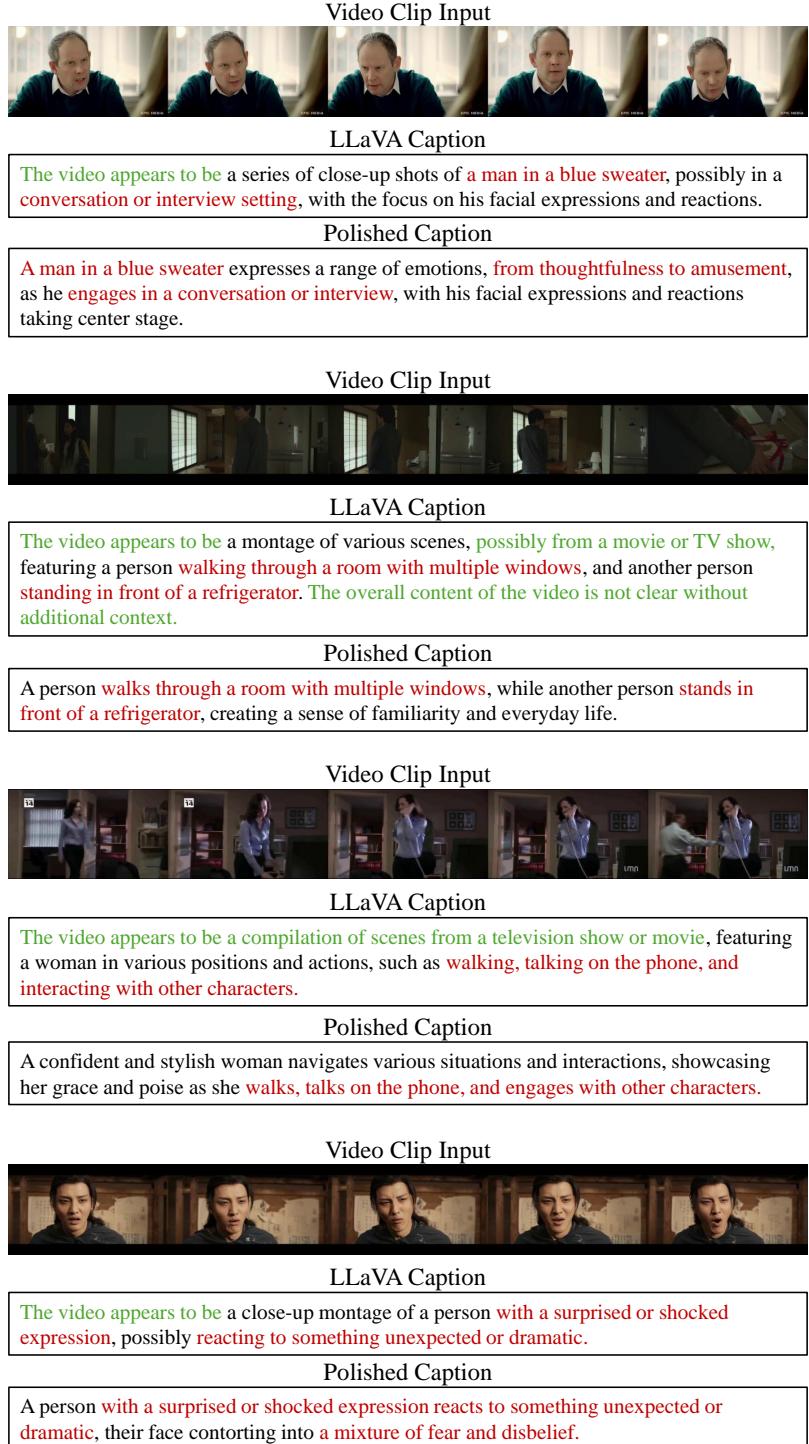


Figure 14: While using LLaVA as the backbone model for our video caption, we find that it contains a lot of "Oral habit", as highlighted in green text in this figure. We further apply a language model to reception the sentence.

References

- [1] Max Bain, Arsha Nagrani, G  l Varol, and Andrew Zisserman. Frozen in time: A joint video and image encoder for end-to-end retrieval. In *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 1708–1718, 2021.
- [2] Max Bain, Arsha Nagrani, G  l Varol, and Andrew Zisserman. Frozen in time: A joint video and image encoder for end-to-end retrieval. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1728–1738, 2021.
- [3] Satanjeev Banerjee and Alon Lavie. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Jade Goldstein, Alon Lavie, Chin-Yew Lin, and Clare Voss, editors, *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan, June 2005. Association for Computational Linguistics.
- [4] Andreas Blattmann, Tim Dockhorn, Sumith Kulal, Daniel Mendelevitch, Maciej Kilian, Dominik Lorenz, Yam Levi, Zion English, Vikram Voleti, Adam Letts, et al. Stable video diffusion: Scaling latent video diffusion models to large datasets. *arXiv preprint arXiv:2311.15127*, 2023.
- [5] Andreas Blattmann, Robin Rombach, Huan Ling, Tim Dockhorn, Seung Wook Kim, Sanja Fidler, and Karsten Kreis. Align your latents: High-resolution video synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 22563–22575, 2023.
- [6] Haoxin Chen, Menghan Xia, Yingqing He, Yong Zhang, Xiaodong Cun, Shaoshu Yang, Jinbo Xing, Yaofang Liu, Qifeng Chen, Xintao Wang, et al. Videocrafter1: Open diffusion models for high-quality video generation. *arXiv preprint arXiv:2310.19512*, 2023.
- [7] Honglie Chen, Weidi Xie, Andrea Vedaldi, and Andrew Zisserman. Vggsound: A large-scale audio-visual dataset. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 721–725. IEEE, 2020.
- [8] Jun Chen, Deyao Zhu, Kilichbek Haydarov, Xiang Li, and Mohamed Elhoseiny. Video chatcaptioner: Towards the enriched spatiotemporal descriptions. *arXiv preprint arXiv:2304.04227*, 2023.
- [9] Tsai-Shien Chen, Aliaksandr Siarohin, Willi Menapace, Ekaterina Deyneka, Hsiang-wei Chao, Byung Eun Jeon, Yuwei Fang, Hsin-Ying Lee, Jian Ren, Ming-Hsuan Yang, et al. Panda-70m: Captioning 70m videos with multiple cross-modality teachers. *arXiv preprint arXiv:2402.19479*, 2024.
- [10] Xiaowei Chi, Rongyu Zhang, Zhengkai Jiang, Yijiang Liu, Yatian Wang, Xingqun Qi, Wenhan Luo, Peng Gao, Shanghang Zhang, Qifeng Liu, and Yike Guo. M²chat: Empowering vlm for multimodal lilm interleaved text-image generation, 2024.
- [11] Jade Copet, Felix Kreuk, Itai Gat, Tal Remez, David Kant, Gabriel Synnaeve, Yossi Adi, and Alexandre D  fossez. Simple and controllable music generation. *Advances in Neural Information Processing Systems*, 36, 2024.
- [12] SeungHeon Doh, Keunwoo Choi, Jongpil Lee, and Juhan Nam. Lp-musiccaps: Llm-based pseudo music captioning. *arXiv preprint arXiv:2307.16372*, 2023.
- [13] SeungHeon Doh, Keunwoo Choi, Jongpil Lee, and Juhan Nam. Lp-musiccaps: Llm-based pseudo music captioning. *arXiv preprint arXiv:2307.16372*, 2023.
- [14] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale, 2021.
- [15] Jort F Gemmeke, Daniel PW Ellis, Dylan Freedman, Aren Jansen, Wade Lawrence, R Channing Moore, Manoj Plakal, and Marvin Ritter. Audio set: An ontology and human-labeled dataset for audio events. In *2017 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 776–780. IEEE, 2017.
- [16] Yingqing He, Zhaoyang Liu, Jingye Chen, Zeyue Tian, Hongyu Liu, Xiaowei Chi, Runtao Liu, Ruibin Yuan, Yazhou Xing, Wenhui Wang, Jifeng Dai, Yong Zhang, Wei Xue, Qifeng Liu, Yike Guo, and Qifeng Chen. Llms meet multimodal generation and editing: A survey, 2024.
- [17] Yingqing He, Menghan Xia, Haoxin Chen, Xiaodong Cun, Yuan Gong, Jinbo Xing, Yong Zhang, Xintao Wang, Chao Weng, Ying Shan, et al. Animate-a-story: Storytelling with retrieval-augmented video generation. *arXiv preprint arXiv:2307.06940*, 2023.
- [18] Yingqing He, Tianyu Yang, Yong Zhang, Ying Shan, and Qifeng Chen. Latent video diffusion models for high-fidelity long video generation. *arXiv preprint arXiv:2211.13221*, 2022.
- [19] Roberto Henschel, Levon Khachatrian, Daniil Hayrapetyan, Hayk Poghosyan, Vahram Tadevosyan, Zhangyang Wang, Shant Navasardyan, and Humphrey Shi. Streamingt2v: Consistent, dynamic, and extendable long video generation from text. *arXiv preprint arXiv:2403.14773*, 2024.

- [20] Jonathan Ho, William Chan, Chitwan Saharia, Jay Whang, Ruiqi Gao, Alexey Gritsenko, Diederik P Kingma, Ben Poole, Mohammad Norouzi, David J Fleet, et al. Imagen video: High definition video generation with diffusion models. *arXiv preprint arXiv:2210.02303*, 2022.
- [21] Jonathan Ho, Tim Salimans, Alexey Gritsenko, William Chan, Mohammad Norouzi, and David J Fleet. Video diffusion models. *Advances in Neural Information Processing Systems*, 35:8633–8646, 2022.
- [22] Ziqi Huang, Yinan He, Jiashuo Yu, Fan Zhang, Chenyang Si, Yuming Jiang, Yuanhan Zhang, Tianxing Wu, Qingyang Jin, Nattapol Chanpaisit, Yaohui Wang, Xinyuan Chen, Limin Wang, Dahua Lin, Yu Qiao, and Ziwei Liu. VBench: Comprehensive benchmark suite for video generative models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2024.
- [23] Peng Jin, Ryuichi Takanobu, Caiwan Zhang, Xiaochun Cao, and Li Yuan. Chat-univi: Unified visual representation empowers large language models with image and video understanding. *arXiv preprint arXiv:2311.08046*, 2023.
- [24] Kevin Kilgour, Mauricio Zuluaga, Dominik Roblek, and Matthew Sharifi. Fr\`echet audio distance: A metric for evaluating music enhancement algorithms. *arXiv preprint arXiv:1812.08466*, 2018.
- [25] Dan Kondratyuk, Lijun Yu, Xiuye Gu, Jos\'e Lezama, Jonathan Huang, Rachel Hornung, Hartwig Adam, Hassan Akbari, Yair Alon, Vighnesh Birodkar, et al. Videopoet: A large language model for zero-shot video generation. *arXiv preprint arXiv:2312.14125*, 2023.
- [26] Qiuqiang Kong, Yin Cao, Turab Iqbal, Yuxuan Wang, Wenwu Wang, and Mark D Plumbley. Panns: Large-scale pretrained audio neural networks for audio pattern recognition. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 28:2880–2894, 2020.
- [27] Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles. Dense-captioning events in videos. *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 706–715, 2017.
- [28] Yanwei Li, Yuechen Zhang, Chengyao Wang, Zhisheng Zhong, Yixin Chen, Ruihang Chu, Shaoteng Liu, and Jiaya Jia. Mini-gemini: Mining the potential of multi-modality vision language models. *arXiv:2403.18814*, 2023.
- [29] Bin Lin, Bin Zhu, Yang Ye, Munan Ning, Peng Jin, and Li Yuan. Video-llava: Learning united visual representation by alignment before projection. *arXiv preprint arXiv:2311.10122*, 2023.
- [30] Chin-Yew Lin and Franz Josef Och. Automatic evaluation of machine translation quality using longest common subsequence and skip-bigram statistics. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics (ACL-04)*, pages 605–612, Barcelona, Spain, July 2004.
- [31] Han Lin, Abhay Zala, Jaemin Cho, and Mohit Bansal. Videodirectorgpt: Consistent multi-scene video generation via llm-guided planning. *arXiv preprint arXiv:2309.15091*, 2023.
- [32] Ji Lin, Chuang Gan, and Song Han. Tsm: Temporal shift module for efficient video understanding. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 7083–7093, 2019.
- [33] Kevin Lin, Linjie Li, Chung-Ching Lin, Faisal Ahmed, Zhe Gan, Zicheng Liu, Yumao Lu, and Lijuan Wang. Swinbert: End-to-end transformers with sparse attention for video captioning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 17949–17958, 2022.
- [34] Tsung-Yi Lin, Michael Maire, Serge Belongie, Lubomir Bourdev, Ross Girshick, James Hays, Pietro Perona, Deva Ramanan, C. Lawrence Zitnick, and Piotr Doll\'ar. Microsoft coco: Common objects in context, 2015.
- [35] Haotian Liu, Chunyuan Li, Yuheng Li, Bo Li, Yuanhan Zhang, Sheng Shen, and Yong Jae Lee. Llava-next: Improved reasoning, ocr, and world knowledge, January 2024.
- [36] Zhaoyang Liu, Limin Wang, Wayne Wu, Chen Qian, and Tong Lu. Tam: Temporal adaptive module for video recognition. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 13708–13718, 2021.
- [37] Fuchen Long, Zhaofan Qiu, Ting Yao, and Tao Mei. Videodrafter: Content-consistent multi-scene video generation with llm. *arXiv preprint arXiv:2401.01256*, 2024.
- [38] Muhammad Maaz, Hanoona Rasheed, Salman Khan, and Fahad Shahbaz Khan. Video-chatgpt: Towards detailed video understanding via large vision and language models, 2023.
- [39] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 2630–2640, 2019.
- [40] Arsha Nagrani, Paul Hongsuck Seo, Bryan Seybold, Anja Hauth, Santiago Man\'en, Chen Sun, and Cordelia Schmid. Learning audio-video modalities from image captions. In *European Conference on Computer Vision*, 2022.

- [41] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In Pierre Isabelle, Eugene Charniak, and Dekang Lin, editors, *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics.
- [42] Anna Rohrbach, Atousa Torabi, Marcus Rohrbach, Niket Tandon, Christopher Joseph Pal, H. Larochelle, Aaron C. Courville, and Bernt Schiele. Movie description. *International Journal of Computer Vision*, 123:94 – 120, 2016.
- [43] Simon Rouard, Francisco Massa, and Alexandre Défossez. Hybrid transformers for music source separation. In *ICASSP 23*, 2023.
- [44] Ramon Sanabria, Ozan Caglayan, Shruti Palaskar, Desmond Elliott, Loïc Barrault, Lucia Specia, and Florian Metze. How2: A large-scale dataset for multimodal language understanding. *ArXiv*, abs/1811.00347, 2018.
- [45] Christoph Schuhmann, Richard Vencu, Romain Beaumont, Robert Kaczmarczyk, Clayton Mullis, Aarush Katta, Theo Coombes, Jenia Jitsev, and Aran Komatsuzaki. Laion-400m: Open dataset of clip-filtered 400 million image-text pairs, 2021.
- [46] Uriel Singer, Adam Polyak, Thomas Hayes, Xi Yin, Jie An, Songyang Zhang, Qiyuan Hu, Harry Yang, Oron Ashual, Oran Gafni, et al. Make-a-video: Text-to-video generation without text-video data. *arXiv preprint arXiv:2209.14792*, 2022.
- [47] Enxin Song, Wenhao Chai, Guanhong Wang, Yucheng Zhang, Haoyang Zhou, Feiyang Wu, Xun Guo, Tian Ye, Yan Lu, Jenq-Neng Hwang, et al. Moviechat: From dense token to sparse memory for long video understanding. *arXiv preprint arXiv:2307.16449*, 2023.
- [48] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.
- [49] Jonathan C. Stroud, David A. Ross, Chen Sun, Jia Deng, Rahul Sukthankar, and Cordelia Schmid. Learning video representations from textual web supervision. *ArXiv*, abs/2007.14937, 2020.
- [50] Zeyue Tian, Zhaoyang Liu, Ruibin Yuan, Jiahao Pan, Xiaoqiang Huang, Qifeng Liu, Xu Tan, Qifeng Chen, Wei Xue, and Yike Guo. Vidmuse: A simple video-to-music generation framework with long-short-term modeling. *arXiv preprint arXiv:2406.04321*, 2024.
- [51] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.
- [52] Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation, 2015.
- [53] Fu-Yun Wang, Wenshuo Chen, Guanglu Song, Han-Jia Ye, Yu Liu, and Hongsheng Li. Gen-l-video: Multi-text to long video generation via temporal co-denoising. *arXiv preprint arXiv:2305.18264*, 2023.
- [54] Wenjing Wang, Huan Yang, Zixi Tuo, Huigu He, Junchen Zhu, Jianlong Fu, and Jiaying Liu. Videofactory: Swap attention in spatiotemporal diffusions for text-to-video generation. *ArXiv*, abs/2305.10874, 2023.
- [55] Xin Eric Wang, Jiawei Wu, Junkun Chen, Lei Li, Yuan fang Wang, and William Yang Wang. Vatex: A large-scale, high-quality multilingual dataset for video-and-language research. *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 4580–4590, 2019.
- [56] Yi Wang, Yinan He, Yizhuo Li, Kunchang Li, Jiashuo Yu, Xin Jian Ma, Xinyuan Chen, Yaohui Wang, Ping Luo, Ziwei Liu, Yali Wang, Limin Wang, and Y. Qiao. Internvid: A large-scale video-text dataset for multimodal understanding and generation. *ArXiv*, abs/2307.06942, 2023.
- [57] Bo Wu, Shoubin Yu, Zhenfang Chen, Joshua B Tenenbaum, and Chuang Gan. Star: A benchmark for situated reasoning in real-world videos. In *Thirty-fifth conference on neural information processing systems datasets and benchmarks track (Round 2)*, 2021.
- [58] Chao-Yuan Wu, Christoph Feichtenhofer, Haoqi Fan, Kaiming He, Philipp Krahenbuhl, and Ross Girshick. Long-term feature banks for detailed video understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 284–293, 2019.
- [59] Jiannan Xiang, Guangyi Liu, Yi Gu, Qiyue Gao, Yuting Ning, Yuheng Zha, Zeyu Feng, Tianhua Tao, Shibo Hao, Yemin Shi, Zhengzhong Liu, Eric P. Xing, and Zhiting Hu. Pandora: Towards general world model with natural language actions and video states. *arXiv preprint arXiv:2406.09455*, 2024.
- [60] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Msr-vtt: A large video description dataset for bridging video and language. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5288–5296, 2016.
- [61] Hongwei Xue, Tiankai Hang, Yanhong Zeng, Yuchong Sun, Bei Liu, Huan Yang, Jianlong Fu, and Baining Guo. Advancing high-resolution video-language representation with large-scale video transcriptions. *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5026–5035, 2021.

- [62] Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Learning to answer visual questions from web videos. *arXiv preprint arXiv:2205.05019*, 2022.
- [63] Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Zero-shot video question answering via frozen bidirectional language models. *Advances in Neural Information Processing Systems*, 35:124–141, 2022.
- [64] Jiahui Yu, Zirui Wang, Vijay Vasudevan, Legg Yeung, Mojtaba Seyedhosseini, and Yonghui Wu. Coca: Contrastive captioners are image-text foundation models. *Trans. Mach. Learn. Res.*, 2022, 2022.
- [65] Rowan Zellers, Ximing Lu, Jack Hessel, Youngjae Yu, Jae Sung Park, Jize Cao, Ali Farhadi, and Yejin Choi. Merlot: Multimodal neural script knowledge models. In *Neural Information Processing Systems*, 2021.
- [66] Hang Zhang, Xin Li, and Lidong Bing. Video-llama: An instruction-tuned audio-visual language model for video understanding. *arXiv preprint arXiv:2306.02858*, 2023.
- [67] Qiming Zhang, Jing Zhang, Yufei Xu, and Dacheng Tao. Vision transformer with quadrangle attention. *arXiv preprint arXiv:2303.15105*, 2023.
- [68] Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. Bertscore: Evaluating text generation with bert, 2020.
- [69] Minyi Zhao, Bingjia Li, Jie Wang, Wanqing Li, Wenjing Zhou, Lan Zhang, Shijie Xuyang, Zhihang Yu, Xinkun Yu, Guangze Li, et al. Towards video text visual question answering: benchmark and baseline. *Advances in Neural Information Processing Systems*, 35:35549–35562, 2022.
- [70] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric. P Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena, 2023.
- [71] Daquan Zhou, Weimin Wang, Hanshu Yan, Weiwei Lv, Yizhe Zhu, and Jiashi Feng. Magicvideo: Efficient video generation with latent diffusion models. *arXiv preprint arXiv:2211.11018*, 2022.
- [72] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.
- [73] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.