Video-ChatGPT: Towards Detailed Video Understanding via Large Vision and Language Models

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Abstract

Conversation agents fueled by Large Language Models (LLMs) are providing a new way to interact with visual data. While there have been initial attempts for image-based conversation models, this work addresses the underexplored field of *video-based conversation* by introducing Video-ChatGPT. It is a multimodal model that merges a video-adapted visual encoder with a LLM. The resulting model is capable of understanding and generating detailed conversations about videos. We introduce a new dataset of 100,000 video-instruction pairs used to train Video-ChatGPT acquired via manual and semi-automated pipeline that is easily scalable and robust to label noise. We also develop a quantitative evaluation framework for video-based dialogue models to objectively analyse the strengths and weaknesses of video-based dialogue models. Our code, models, instruction set and demo are released at https://github.com/mbzuai-oryx/Video-ChatGPT.

1 Introduction

The surge of deep learning applications for video understanding has lead to major advancements in video-related tasks. However, the current video understanding models are still unable to hold an open-ended conversation about the video content in a coherent manner. A video-based dialogue model can revolutionize video search, surveillance operations and help summarize key events and abnormal event detection. Above all, it can provide a unified human-understandable interface to video-related tasks such as action recognition, localization, detection, segmentation, retrieval, and tracking. Further, such a capability is of great interest as it will demonstrate the model's ability to encode temporal and spatial cues, contextual relationships and long-term dependencies.

Recent advancements in multimodal understanding are largely based on the combination of pretrained *image* models with Large Language Models (LLMs) but generally do not consider video inputs [1–5]. It is therefore interesting to leverage the vast capabilities of LLMs for video understanding tasks in a way that would not only maintain the temporal and spatial characteristics but also be adept at generating human-like conversations about videos. In this paper, we introduce Video-ChatGPT, a novel multimodal model that merges the representational abilities of a pretrained visual encoder and the generative powers of an LLM, capable of understanding and conversing about videos.

Video-ChatGPT leverages an adapted LLM [1] that integrates the visual encoder of CLIP [6] with Vicuna [7] as a language decoder, fine-tuned on generated instructional image-text pairs. Our approach further adapts the desgin for spatiotemporal video modeling and fine-tunes the model on video-instruction data to capture temporal dynamics and frame-to-frame consistency relationships available in video data. In contrast to other concurrent works for video-based conversation [8, 9], Video-ChatGPT excels at temporal understanding, spatial consistency and contextual comprehension as demonstrated by our extensive evaluations.

A fundamental contribution of this work is the creation of a dataset of 100,000 video-instruction pairs using a combination of human-assisted and semi-automatic annotation methods. Each pair consists of

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a video and its associated instruction in the form of a question-answer. This provides Video-ChatGPT with a large and diverse dataset to learn from, increasing its video-specific understanding, attention to temporal relationships and conversation capabilities.

Moreover, we introduce the first quantitative video conversation evaluation framework for benchmarking, allowing for a more accurate evaluation of the performance of video conversation models. This framework evaluates models on a variety of capabilities, such as correctness of information, detail orientation, contextual understanding, temporal understanding, and consistency.

The contributions of this work are as follows,

- We propose Video-ChatGPT, a video conversation model capable of generating meaningful conversations about videos. It combines the capabilities of LLMs with a pretrained visual encoder adapted for spatiotemporal video representations.
- We introduce 100,000 high-quality video instruction pairs together with a novel annotation framework that is scalable and generates a diverse range of video-specific instruction sets.
- We develop the first quantitative video conversation evaluation framework for benchmarking video conversation models. We demonstrate Video-ChatGPT to perform well compared to concurrent conversational engines for videos such as Video Chat [8].

2 Related Work

Vision Language Models: Significant advancements in the field of computer vision have recently been observed due to the development of many foundational vision-language models. These models represent a significant leap towards creating general-purpose vision models capable of tackling various tasks simultaneously [6, 10–12]. A prime example is CLIP [6], which is trained on 400M image-text pairs and has demonstrated impressive zero-shot performance on numerous benchmarks. It has been employed in various downstream applications, from image-based object detection and segmentation [13, 14] to 3D applications [15, 16]. Numerous attempts have also been made to adapt CLIP for video applications [17, 16]. Similar to our design, ViFi-CLIP [18] suggests employing temporal pooling across video frames to adapt the image-based CLIP model for video-based tasks.

Large Language Models: The field of natural language processing has witnessed a paradigm shift with the advent of pretrained Large Language Models (LLMs) such as GPT [19], LLaMA [20], OPT [21], and MOSS [22]. These models exhibit extraordinary abilities like language generation and in-context learning, and their knack for understanding intricate tasks given user prompts in a zero-shot manner reflects their impressive adaptability and generalization. The proven capabilities of LLMs have encouraged researchers to fine-tune them to maximize their proficiency.

A key strategy in this pursuit is instruction tuning. This approach focuses on improving the model's alignment with user intentions and optimizing their output quality. For instance, InstructGPT [23] and ChatGPT [24] significantly benefit from this technique, showcasing improvements in diverse conversational interaction capabilities and their aptitude to answer a broad range of complex questions. This effective approach has recently been employed in open-source models like Alpaca [25] and Vicuna [7], both developed using the LLaMA [20] framework, resulting in performance improvements.

Pre-trained LLMs in Vision-Language Tasks: The recent strides in multimodal understanding have primarily been driven by the integration of image-based vision models with LLMs. Seminal contributions such as Flamingo [10] and BLIP-2 [4] have demonstrated the power of utilizing web-scale image-text data, as well as pioneering techniques in cross-modal alignment, to exhibit dynamic abilities in conversational and few-shot learning contexts. Building on this foundation, MiniGPT-4 [2] allows image-based conversations by integrating BLIP-2 and Vicuna for zero-shot image comprehension.

Equally significant is the emergence of LLaVA [1], a model derived from the LLaMa architecture, leveraging GPT-4's language proficiency to generate multimodal instruction-following data. With instruction tuning applied on the derived data, LLaVA has displayed interesting multimodal chat capability, hinting at the scalability potential of such a methodology. In addition, InstructBLIP [5] model has demonstrated strong image-based dialogue capabilities via vision-language instruction tuning by innovating with instruction-aware visual feature extraction.

More closely related to our work, VideoChat [8] employs selective components of video foundational models [26] and image foundation models [4], and integrates them with LLMs [7] in conjunction
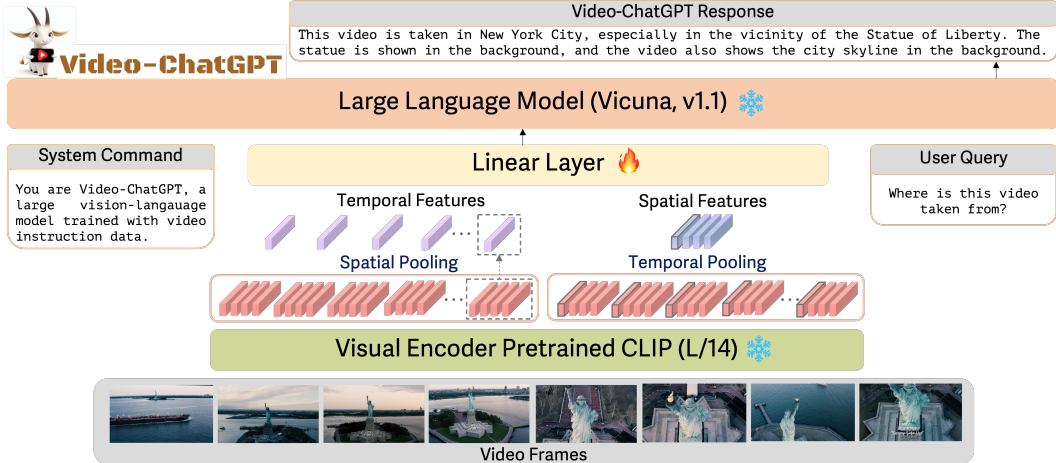
Figure 1: **Architecture of Video-ChatGPT.** Video-ChatGPT leverages the CLIP-L/14 visual encoder to extract both spatial and temporal video features. This is accomplished by averaging frame-level features across temporal and spatial dimensions respectively. The computed spatiotemporal features are then fed into a learnable linear layer, which projects them into the LLMs input space. In our approach, we utilize the Vicuna-v1.1 model, comprised of 7B parameters, and initialize it with weights from LLaVA [1].

with few learnable layers, tuned using a two-stage lightweight training. Additionally, they construct a video-specific dataset using off-the-shelf vision-language models [27, 4, 28, 26] for generating noisy detailed textual descriptions to enhance the training of video-centric conversational models.

Different from VideoChat, we propose a novel human assisted and semi-automatic annotation framework for generation high quality instruction data for videos (see Sec. 4). Our simple and scalable architecture design utilizes pretrained CLIP [6] to generate spatiotemporal features which help Video-ChatGPT in generating meaningful video conversation. Further, we are the first to propose quantitative framework for evaluating video conversation tasks (see Sec. 4).

3 Video-ChatGPT

Video-ChatGPT is a large vision-language model that aligns video representations with a Large Language Model (LLM), thus enhancing its ability to generate meaningful conversation about videos. Our approach draws from the approach employed in designing vision-language (VL) models for the video domain. Given the limited availability of video-caption pairs and the substantial resources required for training on such data from scratch, these models commonly adapt pretrained image-based VL models for video tasks [16–18]. We adopt a similar approach, starting with the Language-aligned Large Vision Assistant (LLaVA)[1] as our foundation.

LLaVA is a LMM that integrates the visual encoder of CLIP [6] with the Vicuna language decoder [7] and is fine-tuned end-to-end on generated instructional vision-language data. We fine-tune this model using our video-instruction data, adapting it for video conversation task. The video-instruction data is obtained as a combination of manual and automated pipelines in our proposed instruction generation setup. This adaptation on video-specific instructions allows for accommodating additional temporal dynamics, frame-to-frame consistency, and long-range relationships present in video data. As a result, our Video-ChatGPT excels in video reasoning, creativity, and understanding of spatial, temporal, and action-oriented components within videos.

3.1 Architecture

We use CLIP ViT-L/14, which is pretrained using large-scale visual instruction tuning in LLaVa, as the visual encoder. However, LLaVa visual encoder is meant for images, which we modify to capture spatiotemporal representations in videos. Given a video sample $V_i \in \mathbb{R}^{T \times H \times W \times C}$ with T frames, the visual encoder generates temporal and spatial features. The visual encoder encodes the T frames independently as a batch of images and produces frame-level embeddings $x_i \in \mathbb{R}^{T \times h \times w \times D}$, where $h = H/p, w = W/p$. Here p is the patch size (*i.e.* 14 for ViT-L/14), and we represent the number of

tokens as N, where $N = h \times w$. Frame-level embeddings are average-pooled along the temporal dimension to obtain a *video-level temporal representation* $t_i \in \mathbb{R}^{N \times D}$. This operation, referred to as temporal pooling, implicitly incorporates temporal learning through the aggregation of multiple frames. Similarly, the frame-level embeddings are average-pooled along the spatial dimension to yield the *video-level spatial representation* $z_i \in \mathbb{R}^{T \times D}$. The temporal and spatial features are concatenated to obtain the video-level features v_i,

$$v_i = [t_i \quad z_i] \in \mathbb{R}^{(T+N) \times D}. \tag{1}$$

A simple trainable linear layer g, projects these video-level features into the language decoder's embedding space, transforming them into corresponding language embedding tokens Q_v,

$$Q_v = g(v_i) \in \mathbb{R}^{(T+N) \times K}. \tag{2}$$

Note that the function g acts as an adapter and can be implemented with more complicated architectures as well. However, we opt for a simplistic design that gives competitive performance compared to more sophisticated choices in our experiments. The text queries are tokenized to the same dimensions, $Q_t \in \mathbb{R}^{L \times K}$. Here L represents the length of text query. Finally, Q_v is concatenated with Q_t and input to the language decoder.

3.2 Video Instruction Tuning

We employ instruction-tuning of the LLM on the prediction tokens, utilizing its original auto-regressive training objective. The pretrained model is finetuned with curated, high-quality video-text pairs. During the finetuning phase, we use predefined prompts based on the following template:

USER: <Instruction> <Vid-tokens> Assistant:

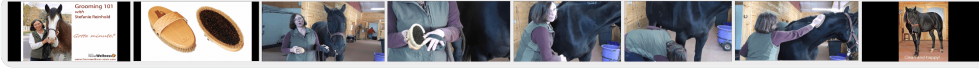Using the notations, we can represent it as,

USER: <Q_t> <Q_v> Assistant:

In this prompt, the <Instruction> represents a question pertaining to the video, randomly sampled from the training set of video-question-answer pairs. Questions can be general, asking to describe the video, or they may relate to specific temporal, spatial, or creative aspects of the video content. The prediction answer <Answer> corresponds to the specific question asked. Throughout the training, the weights for both the video encoder and LLM remain frozen, and the model maximizes the likelihood of predicting tokens representing the answer by adapting the linear layer. Consequently, the video features Q_v become aligned with the pre-trained LLM word embeddings, equipping Video-ChatGPT with the ability to produce more natural and dependable responses.

4 Video Instruction Data Generation

In this section, we discuss our data-focused approach, which uses both human-assisted and semi-automatic annotation methods to generate high-quality video instruction data. This data is crucial for training Video-ChatGPT, making sure the model gives accurate and meaningful responses. Our data collection involves two key methods. The *human-assisted annotation*, involves expert annotators analysing video content and providing detailed descriptions. This process generates data rich in context and detail, which helps our model understand complex aspects of video content. On the other hand, the *semi-automatic annotation framework* is more cost-effective and scalable. Leveraging state-of-the-art vision-language models, this method generates broad, high-volume annotations, thus increasing the quantity of data without compromising the quality substantially. Through these combined methods, we have successfully accumulated a robust set of 100,000 video-instructional pairs. This extensive dataset is crucial in fine-tuning our model to comprehend video content effectively, integrating both spatial and temporal cues into its understanding.

Our instructional data is both diverse and comprehensive, incorporating a wide range of data types. These include detailed descriptions, summarizations, question-answer pairs, tasks that stimulate creativity or generation of new ideas, and conversational tasks. The data spans a broad spectrum of concepts, ranging from visual appearance and temporal relations to complex reasoning tasks and beyond, providing a diverse training ground for our model to learn from.

Original Dataset Annotation:

An intro leads into various pictures of horse tools and a woman speaking to the camera holding a brush. She then brushes the horse's mane thoroughly while still looking to the camera and speaking.

Human Annotated:

The video begins with an intro slide, where there is a picture of the woman standing next to a brown and white horse. The woman is wearing a green jacket over a white shirt. Then an intro leads into various pictures of horse tools and a woman speaking to the camera holding a brush. The video is about "how to groom your horse to shine in four easy steps with a finishing brush. She then brushes the horse's mane thoroughly while still looking at the camera and speaking. The horse is black and the video is shot inside a stable. She wears a green jacket over a long-sleeved purple t-shirt. She is explaining how to use a finishing brush. She shows that the brush has a raised edge, which will help remove more dirt. She uses long strokes to brush the hair of the horse in the direction of hair growth. She cleans from the top to the legs. She then explains that the brush needs to be cleaned with a tool named curry. Finally, the video ends with a picture of the black horse all groomed up and credits to the video.

Original Dataset Annotation:

A close up of a christmas tree is shown followed by close ups of ornaments. Two people are then seen moving around the tree decorating as well as turning the lights off. They finish decorating the tree and playing with one another and laughing. In the end close ups of the trees are shown as well as a bear.

Human Annotated:

In the video, we see a beautifully decorated Christmas tree with lush green branches adorned with bright and colorful ornaments. As the camera pans over the ornaments, they glisten in the light, reflecting the colors of the rainbow. Two people are then shown moving around the tree, hanging ornaments and stringing lights, carefully placing each ornament in its designated spot. As they work, they chat and joke around, enjoying each other's company and the festive spirit. After they finish hanging the ornaments, they step back and admire their work, giggling and hugging each other. The camera captures close-ups of the finished tree, showing off all of its beauty and sparkle. The lights twinkle and glow, casting a warm and cozy ambiance around the room. The scene is one of holiday cheer and joy, a perfect representation of the Christmas spirit. Finally, the camera zooms out and we see a cute little bear toy dancing under the tree, surrounded by beautifully wrapped presents. Overall, the video showcases the joy and warmth of the festive season, with a beautifully decorated tree, love, and the spirit of giving and sharing.

Figure 2: **Examples of data enrichment via human-assisted annotation**. Human annotators augment video descriptions from video-caption datasets. The captions are enriched by integrating detailed information regarding spatial and temporal aspects, relationships, reasoning, scene descriptions, and the chronological sequence of events.

4.1 Human-assisted Annotation

In this process, we leverage datasets containing video-caption pairs and utilize the expertise of human annotators to enrich the original ground truth annotations. Specifically, we use a subset of the ActivityNet-200 [29] dataset which provides concise ground truth descriptions of various activities in distinct video segments.

The annotators further enrich the captions by adding comprehensive information about physical appearances and spatial and temporal localization, among other critical contextual details. Figure 2 shows an example of how a ground truth caption is enriched using human-assisted annotation.

4.2 Semi-automatic Annotation Framework

In addition to the rich human-assisted annotations, we also harness the capabilities of advanced dense image vision-language models, developing a semi-automatic annotation framework. This approach is cost-effective and scalable, thereby increasing the quantity of data without substantially compromising the quality.

Similar to the human-assisted process, this framework also leverages datasets containing video-caption pairs. We enrich these datasets using contextual information drawn from off-the-shelf dense prediction and captioning image-based vision-language models. These models provide predictions that deliver additional contextual information, thereby enriching the video captions. We crafted developed a comprehensive method that combines these predictions, and utilize specific models for the purpose of eliminating noisy or irrelevant context from the data. This ensures that the data maintains its accuracy and relevance.

Building on the use of off-the-shelf models, we apply pretrained models like BLIP-2[4] and GRiT [27] for key-frame analysis in the videos. The BLIP-2 image-captioning model generates frame-level captions, while the GRiT dense captioning model provides detailed captions for scene objects. Additionally, the pretrained Tag2Text [28] model is used to generate tags for each key-frame of the video. Despite their utility, these models can introduce noise into the data.

Original Dataset Annotation:

A countdown is shown followed by a woman catching balls thrown at her. The number counts down more and shows more clips of women playing dodgeball. Several more numbers and clips are shown ending with people performing impressive throws.

Semi-Automatically Annotated:

The video starts with a countdown, and as the numbers decrease, we see a woman standing in an arena. Suddenly, multiple balls are thrown at her from different directions, and we see her successfully catch them one by one with great agility and precision. As the countdown continues, we see more clips of women playing dodgeball in the same arena, demonstrating their skills in avoiding being hit by the balls. The countdown continues to show more numbers and clips of people playing dodgeball. We see players on different teams with colorful jerseys, throwing balls at their opponents and trying to avoid getting hit themselves. In some of the clips, we see players making impressive throws, spinning and turning before they release the ball, which adds to the excitement of the game. Towards the end of the video, we see people performing some incredible throws, bouncing the ball off the floor or walls before hitting their targets. The video ends with a final impressive move, where someone jumps from a trampoline and throws the ball with great power and accuracy. Overall, the video showcases the excitement, skills, and competitiveness of the game of dodgeball, emphasizing the agility and precision required to play it successfully.

Original Dataset Annotation:

Several individuals play against each other in a table football match. Two individuals walk by in the background. Another two individuals walk by in the background.

Semi-Automatically Annotated:

This video features a table football match between several individuals. In the background, we can see two individuals walking by, followed by another two individuals. The main focus of the video is the intense match taking place on the table football. The players seem to be engaged in a competitive game, with each team trying to score as many goals as possible. The players are constantly moving their rods back and forth, trying to defend their goal and score against their opponents. As we observe the video, we can see that it takes place indoors, presumably in a recreational center or someone's home. The noise level is moderate, with the sounds of the table football game and quiet conversations in the background. The lighting is adequate, with a soft yellowish glow coming from ceiling lights. The table football itself is a standard one, with green color cloth and black and white football players. In conclusion, this video is a portrayal of an enthusiastic and competitive table football game, with several individuals trying their best to defeat their opponents. The peripheral characters in the background make it evident that the video takes place indoors, most probably in a recreational setting.

Figure 3: **Examples of data enrichment using our proposed semi-automatic annotation.** We employ off-the-shelf dense prediction and captioning models to augment video descriptions. The BLIP-v2 [4] model generates frame-level captions, while GRIT [27] is utilized for dense frame captions. Tag2Text [28] model generates tags for each key-frame, aiding in eliminating noise. All additional context elements are combined with the video captions and undergo a GPT-assisted post-processing stage, generating the final detailed description.

To ensure high-quality data and mitigate noise, we implement three key steps. First, we maintain a high prediction threshold for all off-the-shelf models to uphold accuracy. Second, we employ a specialized filtering mechanism that removes any frame-level caption from BLIP-2 or GRiT not matching with the Tag2Text frame-level tags. This process involves extracting words from the frame-level captions that are within the predefined Tag2Text tags vocabulary, and eliminating any captions that contain words not in the tags for a given frame. This strategy acts as an additional filtering layer, enriches the captions by integrating predictions from multiple models.

In the third step, we merge frame-level captions and use the GPT-3.5 model to generate a singular, coherent video-level caption. This step augments the original ground truth caption with context from these models. We also direct GPT-3.5 to discard inconsistent information across frames, ensuring a precise, contextually rich video instruction dataset. Figure 3 illustrates how a ground truth caption is enriched using this process after all three refinement stages.

4.3 GPT-Assisted Postprocessing

Lastly, we implement a GPT-Assisted Postprocessing mechanism that refines and optimizes the enriched annotations, in order to generate high-quality video instructional data. We prompt GPT-3.5 model to create question-answer pairs from the enriched and detailed captions that cover a wide variety of aspects. These aspects include detailed descriptions, summarizations, question-answer pairs, tasks that stimulate creativity or the generation of new ideas, and conversational tasks.

Each of these elements plays a crucial role in our data-centric approach. Our ultimate goal is to create a video-based conversation model that is accurate, capable of understanding video content from both spatial and temporal cues, and adept at engaging in conversations.

5 Experiments

5.1 Implementation Details

We use LLaVA as our baseline model and finetune it on 100K video instruction pairs. We only update the linear layer projecting the video features to the LLMs' input space, while the rest of the architecture is kept frozen. We finetune the model for 3 epochs using a learning rate of $2e^{-5}$ and an overall batch size of 32. The training of our 7B model took around 3 hours on 8 A100 40GB GPUs. During inference, for memory efficiency, we load the models in FP16 mode.

In our semi-automatic annotation framework, we use Katna [30] to extract the video key-frames. For the off-the-shelf Tag2Text [28] model, we use the Swin-B version with input size of 384×384 and confidence threshold of 0.7. For GRIT [27], we use ViT-B version with CenterNet2 [31].

5.2 Quantitative evaluation

In this section, we highlight a key contribution of our work: the quantitative evaluation of Video-ChatGPT using advanced metrics and comparative evaluations with existing state-of-the-art models. We conduct two types of quantitative evaluations: i) Video-based Generative Performance Benchmarking and ii) Zero-Shot Question-Answer Evaluation.

Evaluation Aspect	Video Chat	Video-ChatGPT
Correctness of Information	2.25	2.50
Detail Orientation	2.50	2.57
Contextual Understanding	2.54	2.69
Temporal Understanding	1.98	2.16
Consistency	1.84	2.20

Table 1: **Performance benchmarking of text generation models.** An in-depth comparative analysis of Video-ChatGPT and Video Chat [8] across five key evaluation aspects we propose in our benchmark. Video-ChatGPT shows competent performance across all key aspects.

Video-based Text Generation Performance Benchmarking: We introduce a benchmark to evaluate the text generation performance of video-based conversation models. To do this, we curate a test set based on the ActivityNet-200 dataset [29], featuring videos with rich, dense descriptive captions and associated question-answer pairs from human annotations. We also develop an evaluation pipeline using the GPT-3.5 model. This pipeline assesses various capabilities of the model and assigns a relative score to the generated predictions on a scale of 1-5, in the following five aspects:

(i) *Correctness of Information:* We verify the accuracy of the generated text, ensuring it aligns with the video content and doesn't misinterpret or misinform.

(ii) *Detail Orientation:* We evaluate the depth of the model's responses, looking for both completeness, meaning the model's response covers all major points from the video, and specificity, denoting the inclusion of specific details rather than just generic points in the model's response.

(iii) *Contextual Understanding:* We assess the model's understanding of the video's context, checking if its responses aligns with the overall context of the video content.

(iv) *Temporal Understanding:* We examine the model's grasp of the temporal sequence of events in the video when answering questions.

(v) *Consistency:* We evaluate the model's consistency across different but similar questions or different sections of the video.

We present the results of the evaluation of our proposed model, Video-ChatGPT, using the quantitative benchmarking framework in Table 1. The results reveal its competent performance across all key aspects when compared with the recently introduced contemporary video conversation model, Video Chat [8]. Video-ChatGPT shows good performance, largely due to the instruction tuning we perform and its straightforward architecture that leverages LLMs with a pretrained visual encoder fine-tuned for video data. This provides it with the robust ability to generate contextually relevant, detailed, and temporally accurate text from video input.

Model	MSVD-QA		MSRVTT-QA		TGIF-QA		Activity Net-QA	
	Accuracy	Score	Accuracy	Score	Accuracy	Score	Accuracy	Score
FrozenBiLM	32.2	–	16.8	–	41.0	–	24.7	–
Video Chat	56.3	2.8	45.0	2.5	34.4	2.3	26.5	2.2
Video-ChatGPT	**64.9**	**3.3**	**49.3**	**2.8**	**51.4**	**3.0**	**35.2**	**2.7**

Table 2: **Zeroshot question-answering** comparison of Video-ChatGPT with other video generative models. Video-ChatGPT performs competitively across all datasets.

Zero-Shot Question-Answer Evaluation: We conducted a comprehensive quantitative evaluation using several commonly used open-ended question-answer datasets: MSRVTT-QA [32], MSVD-QA [32], TGIF-QA FrameQA [33], and ActivityNet-QA [34]. These evaluations were carried out in a zero-shot manner, employing GPT-assisted evaluation to assess the model's capabilities. This evaluation process measures the accuracy of the model's generated predictions and assigns a relative score on a scale of 1-5.

To benchmark Video-ChatGPT, we compared its performance with other significant models, such as FrozenBiLM [35] and the generative video model, Video Chat. FrozenBiLM is a model that adapts frozen bidirectional language models pretrained on Web-scale text-only data to multi-modal inputs, showing promising results in zero-shot VideoQA settings. Despite the solid foundation established by these models, Video-ChatGPT consistently outperformed them, achieving state-of-the-art (SOTA) performance across all datasets. These results indicate Video-ChatGPT's ability to understand video content and generate accurate, contextually rich answers to questions.

5.3 Qualitative Evaluation

We performed an extensive evaluation of our model on a variety of open-ended video question-answering tasks, utilizing diverse videos sourced from ActivityNet and YouTube. The evaluation tasks included video reasoning (Figure 4), creative and generative tasks (see Figure 5), spatial understanding (Figure 6), action recognition (Figure 7), video conversation (Figure 8), question answering (Figure 9) and temporal understanding (Figure 10). Our model demonstrates proficiency in comprehending the content of the videos and generating accurate responses across multiple video based task. Our model can effectively understand the visual information present in the videos and provide precise answers (see Figures 4 to 10).

6 Conclusion and Future Directions

In this work, we presented Video-ChatGPT, a multimodal model that merges a pretrained visual encoder with a large language model (LLM) to enable video understanding and conversations based on videos. Video-ChatGPT leverages an adapter on top of pretrained LLM and vision backbones and is fine-tuned on video-instruction data to capture temporal dynamics and spatial consistency relationships in spatiotemporal sequences. A dataset of 100,000 video-instruction pairs is created to enhance Video-ChatGPT's video-specific understanding and conversation capabilities. The work also introduced a quantitative video conversation evaluation framework for benchmarking, evaluating models on a diverse set of capabilities including conventional video question answering as well as open-ended descriptions. While the model performs competitively in several scenarios, we note it finds it challenging to understand subtle temporal relationships and the visual details of small objects. As a future work, Video-ChatGPT can be extended to simultaneously deal with multiple modalities and to enhance its video comprehension capabilities towards an all-in-one dialogue agent for universal visual content understanding.

Figure 4: **Video Reasoning Task.** This figure illustrates an example from Video-ChatGPT's demonstration showcasing its performance in video reasoning tasks.

Figure 5: **Creative and generative tasks**. Illustrative examples from Video-ChatGPT's demonstration highlighting its performance in video-based creative and generative tasks, such as crafting a story, poem, or advertisement.
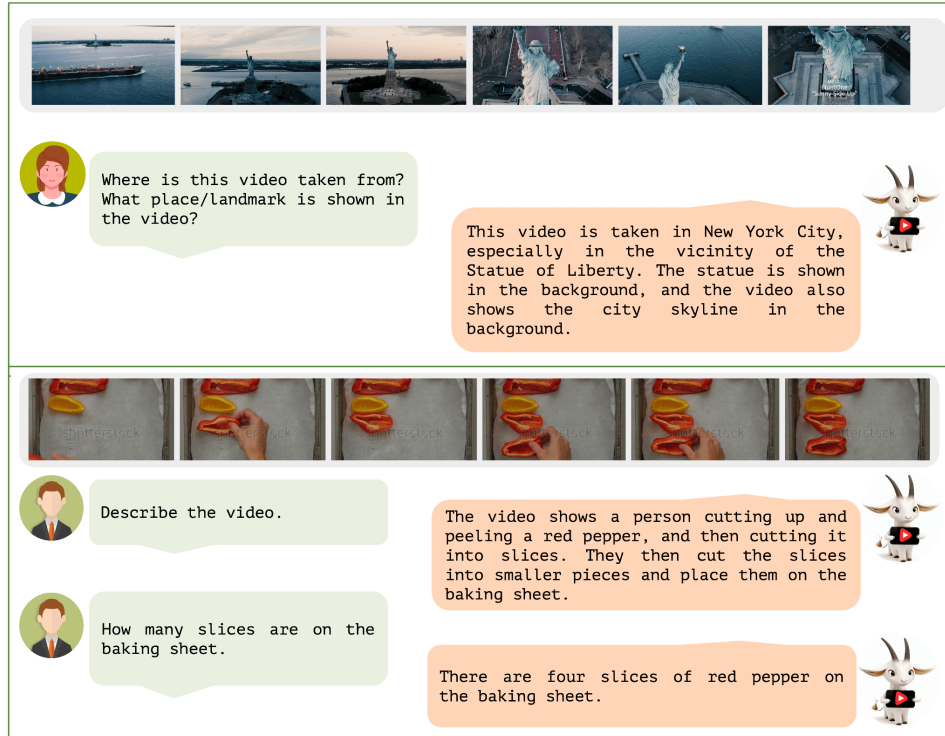
Figure 6: **Spatial understanding tasks.** The figure depicts examples from Video-ChatGPT's demonstration, emphasizing its capability in video-based spatial understanding tasks, including identifying renowned locations or counting the number of objects in a scene.
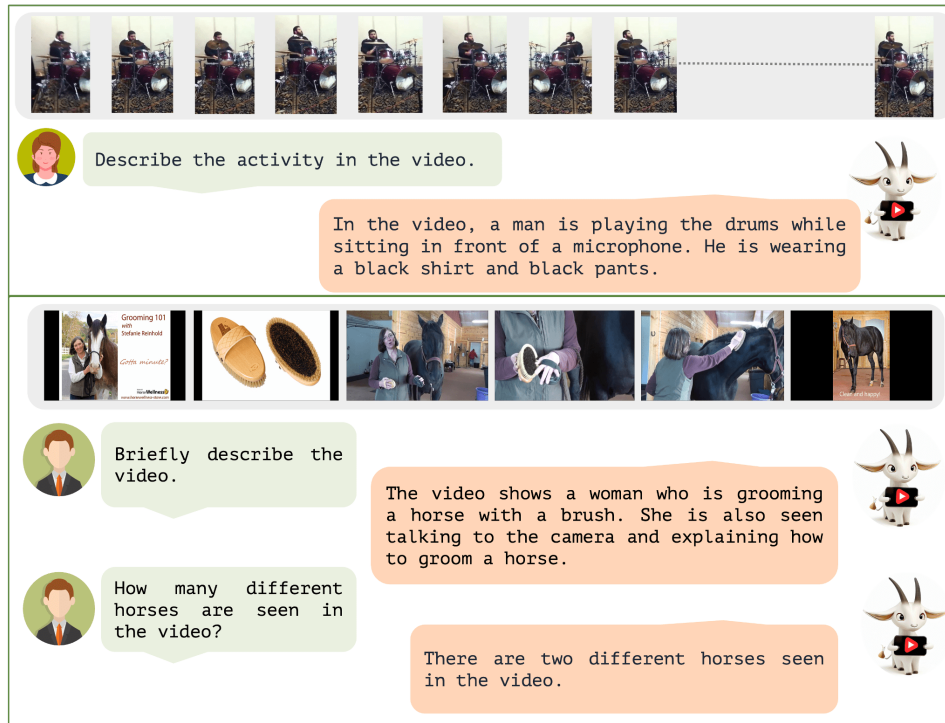

Figure 7: **Actiong Recognition Task.** This figure illustrates examples from Video-ChatGPT's demonstration showcasing its performance in video action recognition tasks such as playing drums and grooming horse.

Describe the video in detail.

The video shows a man cleaning snow off his car using a snow brush. He starts by brushing the snow off the hood of his car, then moves on to the windshield and finally the side mirrors. He uses a snow brush to remove the snow from the car's surface.

What is the main focus of the video.

The main focus of the video is the process of drawing a tree on a white canvas. The artist starts by drawing a trunk, then adds branches and leaves.

What does the woman use to split the logs and how does she do it?

The woman uses a large axe to split the logs. She starts by placing the axe on the log and then swings it down with a powerful motion. The axe slices through the log with ease, and the woman continues to swing it until the log is split in half.

What is the women wearing in the video?

The woman is wearing a black jacket in the video.

Describe the video.

The video shows a young girl performing a gymnastics routine on a balance beam. She starts by walking onto the beam and then performs a series of flips and spins, ending with a handstand. She then walks off the beam and smiles at the camera.

Is there a flag in the background?

Yes, there is an American flag in the background of the video.

Figure 8: **Video Understanding and Conversation Tasks.** This figure illustrates examples from Video-ChatGPT's demonstration showcasing its performance in video understanding and conversation tasks.

Figure 9: **Question-Answering Task.** The figure depicts examples Video-ChatGPT's demonstration showcasing its performance in question-answering tasks.

Describe the video in detail.

The video shows a man standing on a snowy field, throwing a javelin. He throws the javelin and then runs towards it, picking it up and throwing it again. He then runs towards the javelin and picks it up, growing it once more. The man then runs towards the javelin and picks it up, throwing it for the fourth time. The video ends with the man running towards the javelin and picking it up, throwing it for the fifth time.

What is the video about?

The video is about two men who are playing a game of arm wrestling. The video shows the two men trying to push each other's hands down on the table.

What happens after the match is over?

After the match is over, the two men shake hands, showing good sportsmanship and camaraderie.

Can you describe the process for cleaning a screen window as demonstrated in the video?

The video shows a man using a squeegee to clean a window. He starts by wetting the squeegee with water and then rubbing it on the window. He then moves the squeegee across the window, removing any dirt or debris. After cleaning the window, he wipes it dry with a cloth. The man then repeats the process for the other side of the window.

Step-by-step describe the cooking recipe shown in the video.

The video shows a person cooking a dish in a pan. They add ingredients such as noodles such as noodles, and spices to the pan, and then stir the mixture. The person then pours a sauce into the pan and stirs it until it thickens. Finally, they add some more ingredients and stir the mixture again. The dish is then served on a plate.

Figure 10: **Temporal Understanding Task.** The figure provides examples from Video-ChatGPT's demonstration, highlighting its performance in temporal understanding tasks, particularly in comprehending sequences of events.

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