

# Video Understanding with Large Language Models: A Survey

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## Abstract

With the burgeoning growth of online video platforms and the escalating volume of video content, the demand for proficient video understanding tools has intensified markedly. With Large Language Models (LLMs) showcasing remarkable capabilities in key language tasks, this survey provides a detailed overview of the recent advancements in video understanding harnessing the power of LLMs (Vid-LLMs). The emergent capabilities of Vid-LLMs are surprisingly advanced, particularly their ability for open-ended spatial-temporal reasoning combined with commonsense knowledge, suggesting a promising path for future video understanding. We examine the unique characteristics and capabilities of Vid-LLMs, categorizing the approaches into four main types: LLM-based Video Agents, Vid-LLMs Pretraining, Vid-LLMs Instruction Tuning, and Hybrid Methods. Furthermore, this survey also presents a comprehensive study of the tasks and datasets for Vid-LLMs, along with the methodologies employed for evaluation. Additionally, the survey explores the expansive applications of Vid-LLMs across various domains, thereby showcasing their remarkable scalability and versatility in addressing challenges in real-world video understanding. Finally, the survey summarizes the limitations of existing Vid-LLMs and the directions for future research. For more information, we recommend readers visit the repository at <https://github.com/yunlong10/Awesome-LLMs-for-Video-Understanding>.

**Key Words:** Video Understanding, Large Language Model, Vision-Language

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# 1 Introduction

We live in a multimodal world where video has become the most common form of media, thanks in part to the advancement of Internet technology, especially mobile Internet technology. With the rapid expansion of online video platforms and the increasing popularity of cameras in surveillance, entertainment, and automatic driving, video content has emerged as a crucial and engaging medium, surpassing conventional forms of text and combined image-text in terms of richness and appeal. This advancement has promoted an exponential surge in video production, with millions of videos being created daily. However, manually processing this sheer volume of video content is laborious and time-consuming. Consequently, there is a growing demand for tools that can effectively manage, analyze, and process this abundance of video content. To meet this demand, video understanding and analysis technology has emerged, leveraging intelligent analysis techniques. This technology aims to automatically recognize and interpret video content, thereby alleviating the burden on human operators.

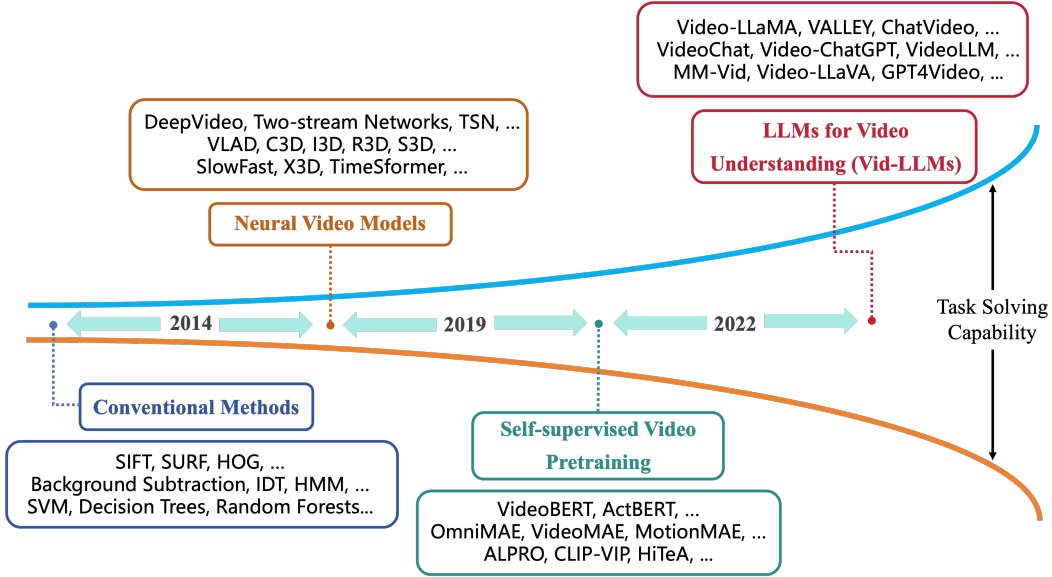


Figure 1: The development of video understanding methods can be summarized into four stages: (1) Conventional Methods, (2) Neural Video Models, (3) Self-supervised Video Pretraining, and (4) Large Language Models for Video Understanding, i.e., Vid-LLMs.

As shown in Figure 1, the evolution of video understanding methods can be divided into four stages:

**Conventional Methods.** In the early stages of video understanding, handcrafted feature extraction techniques such as Scale-Invariant Feature Transform (SIFT) [1], Speeded-Up Robust Features (SURF) [2], and Histogram of Oriented Gradients (HOG) [3] were used to capture key information in videos. Background subtraction [4], optical flow methods [5], and Improved Dense Trajectories (IDT) [6, 7] were used to model the motion information for tracking. Since videos can be viewed as time-series data, time-series analysis techniques like Hidden Markov Models (HMM) [8] were also used to understand video content. Before the popularity of deep learning, basic machine learning algorithms such as Support Vector Machines (SVM) [9], Decision Trees, and Random Forests were also used in video classification and recognition tasks. Cluster analysis [10] for classifying video segments, or Principal Component Analysis (PCA) [11, 12] for data dimensionality reduction were also commonly used methods for video analysis.

**Neural Video Models.** Compared with classical methods, deep learning methods for video understanding possess superior task-solving capabilities.

DeepVideo [13] was the earliest method introducing a deep neural network, specifically a Convolutional Neural Network (CNN), for video understanding. However, the performance was not superior to the best handcrafted-feature method due to the inadequate use of motion information. Two-stream networks [14] combined both CNN and IDT to capture the motion information to improve

the performance, which verified the capability of deep neural networks for video understanding. To handle long-form video understanding, Long Short-Term Memory (LSTM) was adopted [15]. Temporal Segment Network (TSN) [16] was also designed for long-form video understanding by analyzing video segments individually and then aggregating them. Based on TSN, Fisher Vectors (FV) encoding [17], Bi-linear encoding [18], and Vector of Locally Aggregated Descriptors (VLAD) [19] encoding were introduced [20]. These methods improved performance on the UCF-101 [21] and HMDB51 [22] datasets. Different from Two-stream networks, 3D networks started another branch by introducing 3D CNN to video understanding (C3D) [23]. Inflated 3D ConvNets (I3D) [24] utilizes the initialization and the architecture of 2D CNN, Inception [25], to gain a huge improvement on the UCF-101 and HMDB51 datasets. Subsequently, people began employing the Kinetics-400 (K-400) [26] and Something-Something [27] datasets to evaluate the model’s performance in more challenging scenarios. ResNet [28], ResNeXt [29], and SENet [30] were also adapted from 2D to 3D, resulting in the emergence of R3D [31], MFNet [32], and STC [33]. To improve the efficiency, the 3D network has been decomposed into 2D and 1D networks in various studies (e.g., S3D [34], ECO [35], P3D [36]). LTC [37], T3D [38], Non-local [39], and V4D [40] focus on long-form temporal modeling, while CSN [41], SlowFast [42], and X3D [43] tend to attain high efficiency. The introduction of Vision Transformers (ViT) [44] promotes a series of prominent models (e.g., TimeSformer [45], VidTr [46], ViViT [47], MViT [48]).

**Self-supervised Video Pretraining.** Transferability [49, 50] in self-supervised pretraining models [51] for video understanding allows them to generalize across diverse tasks with minimal additional labeling, overcoming the early deep learning models’ need for extensive task-specific data. VideoBERT [52] is an early attempt to perform video pre-training. Based on the bidirectional language model BERT [53], pertaining tasks are designed for self-supervised learning from video-text data. It tokenizes video features with hierarchical k-means. The pre-trained model can be fine-tuned to handle multiple downstream tasks, including action classification and video captioning. Following the “*pre-training*” and “*fine-tuning*” paradigm, a large number of studies on pre-trained models for video understanding, especially video-language models, have emerged. They either use different architectures (ActBERT [54], Masked Autoencoders as Spatiotemporal Learners [55], OmniMAE [56], VideoMAE [57], MotionMAE [58]) or pre-training and fine-tuning strategies (MaskFeat [59], VLM:task-agnostic [60], ALPRO [61], all-in-one transformer [62], maskViT [63], CLIP-ViP [64], Revealing Single Frame Bias for Video-and-Language Learning [65], LF-VILA [66], EMCL [67], HiTeA [68], CHAMPAGNE [69]).

**Large Language Models for Video Understanding.** Recently, large language models (LLMs) have advanced rapidly [70]. The emergence of large language models pre-trained on extensive datasets has introduced a novel in-context learning capability [71]. This allows them to handle a variety of tasks using prompts without the need for fine-tuning. ChatGPT [72] is the first groundbreaking application built on this foundation. This includes capabilities like generating code and invoking tools or APIs of other models for their use. Many studies are exploring to use of LLMs like ChatGPT to call vision models APIs to solve the problems in the computer vision field, including Visual-ChatGPT [73]. The advent of instruct-tuning has further enhanced these models’ ability to respond effectively to user requests and perform specific tasks. LLMs integrated with video understanding capabilities offer the advantage of more sophisticated multimodal understanding, enabling them to process and interpret complex interactions between visual and textual data. Similar to their impact in Natural Language Processing (NLP) [74], these models act as more general-purpose task solvers, adept at handling a broader range of tasks by leveraging their extensive knowledge base and contextual understanding acquired from vast amounts of multimodal data. This allows them to not only understand visual content but also reason about it in a way that is more aligned with human-like understanding. Many works also explore using LLMs in video understanding tasks, namely, Vid-LLMs.

Previous survey papers either study specific sub-tasks in the area of video understanding or focus on methodologies beyond video understanding. For example, [75] surveys multimodal foundation models for general vision-language tasks, which includes both image and video applications. [76] and [77] focuses on surveying video captioning and video action recognition tasks, respectively. Other video understanding tasks such as the video question answering and grounding are not considered. Moreover, [78] and [79] surveyed video-related methodologies – video diffusion models and LLMs, respectively, lacking the concentration on video understanding. Despite the significant value to the community, previous survey papers leave a gap in surveying the general video understanding task

based on large language models. This paper fills this gap by making a comprehensive survey on the video understanding task using large language models.

This survey is structured as follows: Section 2 offers a comprehensive overview, emphasizing methods that harness the capabilities of LLMs and detailing the specific tasks and datasets these methods address. In Section 3, we delve into details of recent researches leveraging LLMs for video understanding, presenting their unique approaches and impact in the field. Section 4 offers a detailed summary and analysis of various tasks, their associated datasets, and evaluation metrics. Section 5 explores the application of Video-LLMs across multiple significant fields. The survey concludes in Section 6 by summarizing key findings and identifying unresolved challenges and potential areas for future research.

In addition to this survey, we have established a GitHub repository that aggregates various supporting resources for video understanding with large language models (Vid-LLMs). This repository, dedicated to enhancing video understanding through Vid-LLMs, can be accessed at [Awesome-LLMs-for-Video-Understanding](#).

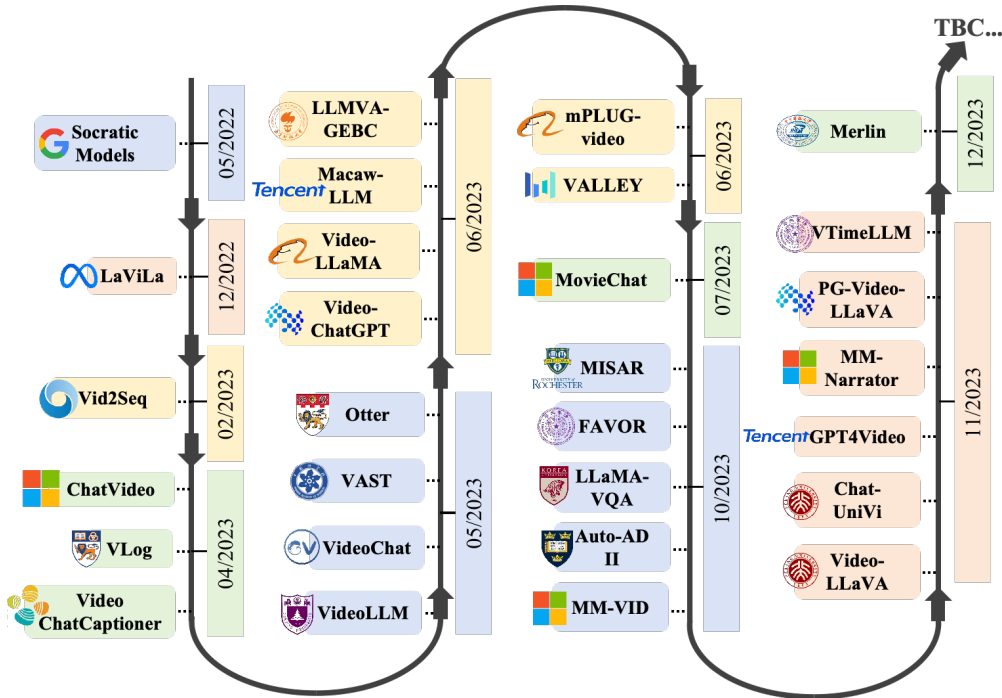


Figure 2: A comprehensive timeline depicting the development of video understanding methods with large language models (Vid-LLMs) over the recent months.

## 2 Foundations

Video understanding is a challenging task that has inspired the creation of numerous innovative tasks aimed at augmenting a model’s capability to interpret video content. From the foundational task of video classification and action recognition, which categorizes videos into predefined classes, the field has evolved to include more intricate tasks. These range from captioning videos with detailed descriptions, to video question answering. The latter not only demands an understanding of the video content but also requires reasoning about logical and commonsense knowledge to formulate responses. As we advance in this field, tasks are becoming increasingly complex and challenging, necessitating models that can interpret videos as intuitively as humans do. We summarize the main tasks in video understanding as follows:

**Recognition and Anticipation.** These tasks form a cohesive duo in video understanding, emphasizing the temporal continuity and progression in videos.

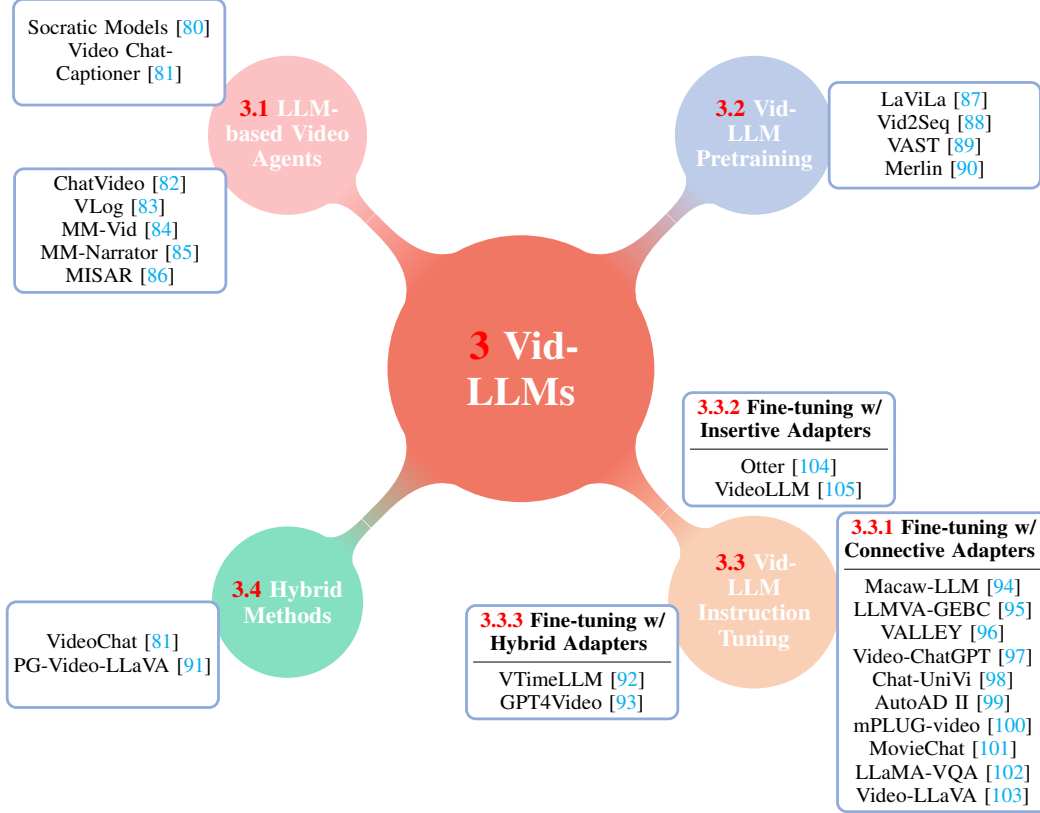


Figure 3: Taxonomy of Video Understanding with Large Language Models (Vids-LLM). The recent Vid-LLMs can be categorized into four major types: LLM-based Video Agents, Vid-LLMs Pretraining, Vid-LLMs Instruction Tuning, and Hybrid Methods. Among these, Instruction Tuning can be further divided into three subcategories based on the type of adapter used: connective, insertive, and a combination of both.

**Captioning and Summarization.** Focusing on more fine-grained details, these tasks involve providing accurate and specific textual descriptions of each moment and distilling the essence of the video, capturing the overarching themes and key narratives. These tasks offer both a micro and macro understanding of video content, combining detail-oriented insights with a broader perspective.

**Grounding and Retrieval.** Seamlessly linking visual content with textual context, tasks falling under this category require the model to identify specific videos or segments that accurately correspond to provided textual descriptions.

**Question Answering.** These tasks emphasize the model’s proficiency in not only comprehending the visual and auditory components of the video but also in integrating external knowledge and reasoning capabilities to deliver contextually relevant answers.

With the advancement of the challenging tasks, the progression of models mirrors the escalating complexity of the tasks they are designed to tackle. From the classical methods that processed a limited number of frames for categorizing videos into predefined labels, reflecting a narrow scope of understanding, to the advent of more sophisticated models, there has been a dramatic expansion in the horizon of video categorization. Modern large models are now capable of ingesting hundreds of frames, enabling them to not only generate detailed text descriptions but also respond to intricate questions about the video content. This leap in capabilities signifies a major shift from task-specific, classical methods that often struggled with generalization to a more versatile and comprehensive approach. The integration of LLMs into video understanding is currently spearheaded by four principal strategies:



**LLM-based Video Agents.** In this approach, LLMs serve as the central controllers. They guide vision models to effectively translate visual information from videos into the language domain. This includes providing detailed text descriptions and transcribing audio elements.

**Vid-LLM Pretraining.** This method focuses on utilizing supervised or contrastive training techniques to develop a foundational video model from the ground up. In this framework, LLMs function as both the encoder and the decoder, offering a comprehensive approach to video understanding.

**Vid-LLM Instruction Tuning.** This strategy involves constructing specialized tuning datasets to refine the integration of vision models with LLMs, specifically tailored for the video domain.

**Hybrid Methods.** These strategies leverage vision models to provide additional feedback during the fine-tuning process. This collaborative approach enables the model to acquire skills beyond text generation, such as object segmentation and other complex video analysis tasks.

Next, we will break down the key components of LLMs and take a closer look at how they work together with foundation models to improve video understanding.

## 2.1 Vision Integration with LLM

To empower LLMs with the ability to interpret video content, there are two primary approaches: (i) utilize pre-trained vision models to extract text information from videos and format them as prompts for LLMs to generate responses. (ii) combines LLMs with vision models with fine-tuning or pre-training strategies to create a unified model that can process video content.

Advanced Large Language Models like GPT-4 have the capability to act as controllers, guiding vision models in executing specific tasks. Within this framework, the vision model primarily functions as a translator, converting visual information into the language domain. Popular choices for vision models include captioners, which provide textual descriptions of entire frames or specific regions, and tagging models provide labels for entities in the view. These models are typically pre-trained on extensive datasets and are readily accessible for integration.

The language information extracted by these vision models is then formulated into prompts for the LLM. This enables the LLM to generate responses or request additional information. The vision model plays a crucial role in this interactive process, providing more detailed or specific information as required by the LLM. This collaboration between the LLM and vision models creates a dynamic system capable of interpreting and responding to complex visual inputs.

In terms of fine-tuning, there are primarily two prevalent categories:

**Frame-Based Encoders.** These encoders handle each video frame independently. The majority in this category are variants of CLIP [106], which are highly regarded for their superior performance and versatility. These variants differ mainly in patch sizes and input resolutions, with a trend toward using higher resolutions for detailed understanding to enhance performance.

**Temporal Encoders.** Temporal Encoders, with TimeSformer [45] as a notable example, approach videos as cohesive entities, emphasizing the temporal elements of the content. Beyond utilizing pre-trained models, some efforts are directed toward developing foundational video models from the ground up with contrastive or supervised pre-training methods, as detailed in Section 3.2.

Given the diverse nature of these video encoders, the length of the input videos they process can vary significantly, ranging from short clips comprising only a few frames to longer videos containing hundreds of frames. To effectively manage this variation, a video modeling module is employed. This module aggregates frame-level features into a cohesive video-level feature. The complexity of this aggregation can range from straightforward pooling methods to more advanced memory-based techniques.

## 2.2 Role of Language in Video Understanding

Language serves as a primary component in video understanding, it mainly includes two aspects: text encoding and decoding.

For text encoding, language models equipped with an encoder, such as BERT [107] or T5 [108], are highly favored in this domain. They are chosen for their robust performance and exceptional

adaptability. In scenarios involving questions or task prompts, the generated text embeddings are often merged with video embeddings to create the input for the decoder. An example of this is the Q-former used in the BLIP-2 model [109]. However, recent advancements like LLaMA [110] have shifted the approach. In these models, text and video are simply tokenized before directly feeding it into the decoder.

There has been a significant shift in the approach to text decoding, moving from specialized transformer models focused on different tasks to pre-trained language models. These large language models vary in size, with some in the Bert family having hundreds of millions of parameters, while those in the LLaMA family [110] may have up to billions of parameters. Built on the Transformer architecture, they operate under an autoregressive framework, predicting the next token in a sequence, which proves effective for text generation. In this realm, the LLaMA family, particularly models like Vicuna, stand out. Vicuna [111], known for its 7B/13B model size, is especially noted for its accessibility and effectiveness in text decoding tasks.

## 2.3 Other Modalities

We distinguish between "audio," which refers to the background sounds in a video, and "speech," which encompasses the spoken content within the video. These elements are often processed independently. Audio and speech are often processed separately, with audio being treated as a single entity and speech being transcribed into text [112]. Speech, on the other hand, is handled by a specialized speech encoder, typically a pre-trained speech recognition model like Whisper [113]. This model transcribes the spoken content into text, providing valuable contextual information for the LLM.

## 2.4 Training Strategies

When tuning pre-trained foundational models to various video understanding tasks, there is often an adapter module which serves as (i) a bridge between the foundation model and the LLM (ii) a module helps pre-trained model to adapt to the new task without losing the knowledge learned from the pre-training. Adapters often function as learnable, parameter-efficient modules that can be added to pre-trained models to extend or adapt their capabilities. A common application of adapters is in converting inputs from various modalities into the text domain, effectively bridging different modalities while keeping the parameters of the pre-trained models, such as encoders and decoders, frozen. One of the key challenges in this process is efficiently translating visual content into text in a manner that is comprehensible to LLM. Popular solutions include linear projection, which aligns the dimensions of visual features with those of text features, and cross-attention mechanisms, like Q-former, that synchronize visual features with related textual content.

Moreover, adapters are also used to tailor the output of LLMs to specific tasks such as selecting an answer from multiple-choice questions. This function is often akin to the role played by a LoRA (Low-Rank Adaptation) module [114], effectively fine-tuning the model's output to suit the particular requirements of a given task.

# 3 Vid-LLMs: Models

In the realm of multimodal large language models (MLLMs), we witness a remarkable unification of large language models with diverse data modalities, ranging from text to images, illustrating their extraordinary versatility and adaptability. These multimodal approaches not only enhance the models' comprehension and reasoning capabilities but also set the stage for the next evolutionary leap in AI: the integration of LLMs with video understanding.

In light of the functionalities of LLMs in video understanding, we categorize Vid-LLM methods into the following categories: (1) LLM-based video agents, (2) Vid-LLM pretraining, (3) Vid-LLM instruction tuning, and (4) hybrid methods.

## 3.1 LLM-based Video Agents

This section explores different video agents based on LLMs, each with its unique approach to integrating multimodal data to enhance video analysis. Some use LLMs to leverage other foundational



Table 1: Comparison of video understanding models with large language models, sorted by their release dates. The table presents key details for each method, including the number of training frames, visual encoders, utilization of audio information, model adaptation approaches, computational resources, the specific large language model employed, and the corresponding number of parameters. Entries marked with a hyphen ("-") indicate undisclosed details in the respective papers.

Model	#Frame	Visual Encoder	Sound Speech	Adapter	Hardware	LLM	#LLM Param.	Date
Socratic Models [80]	Varying	CLIP ViT-L/14@336	✗	Similarity Score	1 NVIDIA V100 GPU	RoBERTa, GPT-3	-	05/2022
LaViLa [87]	4	TimeSformer-B, TimeSformer-L	✗	Cross-Attention	32 V100 GPUs	GPT-2 XL frozen	-	12/2022
Vid2Seq [88]	100	CLIP ViT-L/14@224	✗	Transformer Encoder	64 TPU v4	T5	0.2B	02/2023
Video ChatCaptioner [115]	100	-	✗	BLIP-2	GPU with 24G memory	ChatGPT	20B	04/2023
VLog [83]	-	CLIP ViT-G	✓	-	-	ChatGPT	20B	04/2023
ChatVideo [82]	-	-	✓	-	-	ChatGPT	20B	04/2023
VideoChat [81]	4-32	ViT-G	✗	MLP+Q-former	1 NVIDIA A10 GPU	StableVicuna	7B	05/2023
VAST [89]	4,8	EVAClip-ViT-G, BEATs, BERT-B	✓	-	64 Tesla V100 GPUs	Vicuna	13B	05/2023
Otter [104]	4-8	CLIP ViT-L/14	✗	-	4 RTX-3090 GPUs	LLaMA	7B	05/2023
VideoLLM [105]	Varying	7 Task-Specific Video Encoders	✗	Linear Layer	-	GPT-2, T5, OPT, LLaMA	1.5B/6.5B/6.7B/7B	05/2023
Video-LLaMA [116]	8	CLIP ViT-G	✓	Video Q-former	-	Vicuna	7B	06/2023
Video-ChatGPT [97]	100	CLIP ViT-L/14	✓	Linear Layer	8 A100 40GB GPUs	Vicuna v1.1	7B	06/2023
LLMVA-GEBC [95]	96	CLIP ViT-G	✗	Video Q-former	2 A6000 48G GPUs	OPT	13B	06/2023
mPLUG-video [117]	8	TimeSformer	✗	-	-	GPT/Blood	-	06/2023
VALLEY [96]	Varying	CLIP ViT-L/14	✗	Projection Layer	8 A100 80G GPUs	StableVicuna	7B/13B	06/2023
Macaw-LLM [94]	Varying	CLIP ViT-B/16	✗	Alignment and Integration	-	LLaMA/Vicuna/Bloom	7B	06/2023
MovieChat [101]	2048	CLIP ViT-G/14, EVA-CLIP	✗	Q-former+Long/short-Term Memory	-	GPT-3.5/Claude	-	07/2023
FAVOR [118]	Varying	InstructBLIP ViT-G/14	✓	Causal Q-Former	-	Vicuna	7B/13B	10/2023
Auto-AD II [99]	Varying	CLIP ViT-B/32	✗	-	-	GPT-2	-	10/2023
LLaMA-VQA [102]	-	CLIP ViT-L/14	✗	Linear layer	8 A6000 GPUs	LLaMA	7B	10/2023
LanguageBind [119]	8	ViT-B/32	✓	-	-	OpenCLIP	-	11/2023
Video-LLaVA [103]	8-32	LanguageBind	✓	MLP Projection Layer	-	Vicuna/LLaVA	7B	11/2023
PG-Video-LLaVA [91]	Varying	CLIP ViT-L/14@336	✗	MLP Projection Layer	4 A100 80GB GPUs	Vicuna/LLaVA	7B, 13B	11/2023
VTimeLLM [92]	100	CLIP ViT-L/14	✗	Linear Layer	1 RTX-4090 GPU	Vicuna	7B, 13B	11/2023
Chat-UniVi [98]	64	ViT-L/14, ViT-G	✗	Spatial Temporal Merging	-	Vicuna	7B	11/2023
MM-narrator [85]	Varying	CLIP ViT	✓	-	-	GPT4	-	11/2023
GPT4Video [93]	Varying	CLIP ViT-L/14	✗	Cross-Attention	8 A100 40G GPUs	LLaMA	7B	11/2023
Merlin [90]	8	CLIP ViT-L/14	✗	2D Convolution + 1D Linear Layer	-	Vicuna v1.5	7B	12/2023

models as tools for solving tasks, while others utilize LLMs to process transcriptions from visual, auditory, and textual elements, showcasing their general-purpose task-solving capabilities in video comprehension.

**Socratic Models**[80]. Socratic Models formulate new tasks as a language-based exchange between pretrained models and other modules, all without the need for fresh training or finetuning. Socratic Models model video by integrating visual, auditory, and textual data through a series of structured, language-based prompts to various pretrained models, generating a language-based world-state history. It calculates a proximity metric based on the mean CLIP [106] attributes across all video frames and is benchmarked using the MSR-VTT dataset [120] for video-to-text retrieval. The model supports processing speech, but not sound from videos.

**Video ChatCaptioner** [115]. Video ChatCaptioner is a methodology aimed at producing detailed and comprehensive spatiotemporal descriptions of videos, proposed with a motivation to generate detailed and enriched video descriptions. It enhances video understanding through a dialogue between the ChatGPT [72] and BLIP-2 [109] models. ChatGPT functions as the questioner, tasked with selecting a frame from the sampled frames and generating questions. BLIP-2 responds by providing detailed answers to the inquiries based on the selected video frame. Subsequently, ChatGPT synthesizes the dialogue into comprehensive video captions. Video ChatCaptioner’s performance is evaluated on the MSVD [121] and WebVid [122] datasets. It does not support the processing of sound or speech.

**VLog** [83]. VLog (Video as a Long Document) utilizes a collection of pretrained models to record and interpret visual and audio information from videos. This suite includes BLIP2 for image captioning, GRIT [123] for region-based visual captioning, and Whisper for audio transcription. Whisper [113] is particularly adept at capturing and transcribing speech from videos into precise text, facilitating detailed audio analysis and improved accessibility. Afterwards, ChatGPT is employed to reason over the aggregated data, synthesizing and summarizing the information to enhance understanding and interaction with video content.

**ChatVideo** [82]. ChatVideo operates as a tracklet-centric multimodal video understanding system, integrating ChatGPT with various Video Foundation Models (ViFMs) to label video features, engage in user interactions, and tackle real-world video-related questions and scenarios. Employing a trajectory-focused methodology, ChatVideo interprets video data primarily through the fundamental unit of "tracklet" rather than the conventional frame-by-frame method. ChatVideo processes audio and speech by using Whisper and Wav2Vec 2.0. Overall, ChatVideo performs interactive and multimodal video understanding, enabling enriched video analysis through trackless-centric processing that includes consideration of appearance, motion, and audio aspects, as well as user-driven query interaction.

**MM-Vid** [84]. MM-VID is a system designed for advanced video understanding tasks, including Grounded Question-Answer, Multimodal Reasoning, Hour-Long Video Comprehension, Multi-Video Episodic Analysis, Character Identification, and Audio Description Generation. It models video content by initially using Automatic Speech Recognition (ASR) and scene detection tools to process the video into clips, then employs GPT-4V [124] to generate detailed descriptions of these clips. These descriptions are integrated into a comprehensive script using GPT-4, facilitating a deep understanding of the video. For evaluation, MM-VID was tested on various datasets, including Ego4D [125] for egocentric videos and others featuring diverse video types. The system was fine-tuned and evaluated using these datasets to enhance its capabilities in processing and understanding video content. MM-VID supports the processing of sound and speech inputs, as evidenced by its use of ASR tools and its ability to generate audio descriptions, making videos accessible to individuals with visual impairments. This capability was demonstrated in a user study involving participants with and without visual impairments, using videos with different levels of speech and sound content.

**MM-Narrator** [85]. MM-Narrator is a GPT-4-based system designed for audio description (AD) generation for long-form videos. It handles video understanding tasks by combining multimodal information such as visual features, image captions, and character dialogues from subtitles. The model operates in an autoregressive manner, using a memory-augmented generation process for contextual coherence and character re-identification. It was evaluated on the MAD-eval dataset [99], focusing on AD generation performance. The system includes a complexity-based approach for multimodal in-context learning and a segment-based GPT-4 evaluator. MM-Narrator supports processing both visual and auditory inputs, including sound and speech, for comprehensive video understanding.

**MISAR** [86]. The Multimodal Instructional System with Augmented Reality (MISAR) architecture utilizes the reasoning abilities of GPT-3.5 to improve the video-text captions by gathering contextual information from background knowledge and is designed to process various types of inputs. This includes analyzing video captions, which are generated by a pre-trained video-to-text LLM model consisting of a video Transformer [87] as encoder and GPT-2 [126] as decoder, interpreting recipe instructions and user speech, which is converted to text through Automatic Speech Recognition (ASR) [127], and generating speech using Text-to-Speech (TTS) [128] as a user interface system. GPT-3.5 significantly improves the quality of video captions by refining the initial outputs of the video-to-text model, enhancing relevance and accuracy through advanced language processing capabilities. Integrating sensory inputs with the LLM’s analytical power notably enhances state estimation capabilities within augmented reality environments. Empirical results show a significant improvement in the linguistic alignment of MISAR-generated captions with reference recipes, particularly evident in descriptions of medium-length recipe steps. GPT-3.5’s intervention in the captioning process contributes to this enhancement. However, the current configuration of MISAR has limitations. Errors from the video-to-text model can propagate through the system, and there is a lack of comprehension of environmental audio elements [86]. MISAR uses egocentric video and speech inputs, along with contextual data from language models, to refine state estimation in augmented reality contexts. This approach highlights MISAR’s potential in facilitating users’ performance of physical tasks through a sophisticated synthesis of visual, auditory, and contextual information.

### 3.2 Vid-LLM Pretraining

**LaViLa** [87]. LaViLa can handle multiple multimodal tasks in egocentric videos, including multiple-choice question, multi-instance retrieval, action recognition, and natural language query. It models videos by employing the Narrator and the Rephraser, which are adapted from LLMs. The Narrator is a GPT-2 [126] which is visually conditioned with additional cross-attention modules before each Transformer decoder layer to attend text to visual information, automatically generates dense textual narrations from video clips, focusing on detailed and varied descriptions. The Rephraser, another LLM based on T5-large, augments these narrations by paraphrasing, enhancing text diversity and coverage. The model is trained on video-narration pairs from the Ego4D dataset and evaluated on the Epic-Kitchens, Ego4D, EGTEA [129], and CharadesEgo datasets [130]. The model does not support processing audio or speech from videos.

**Vid2Seq** [88]. Vid2Seq is for dense video captioning. It combines an LLM with special time tokens to simultaneously predict event boundaries and textual descriptions within videos. It concatenates video frame features with text tokens in a sequence. Pre-trained on a vast collection of unlabeled, untrimmed, narrated videos from the YT-Temporal-1B dataset, Vid2Seq leverages pseudo-event boundaries and captions from transcribed speech. It is fine-tuned and evaluated on YouCook2 [131], ViTT [132], ActivityNet Captions, MSR-VTT, and MSVD for dense video captioning, event localization, video paragraph captioning, and video clip captioning. The model is not designed for natural audio input but can deal with speech from videos by ASR.

**VAST** [89]. The VAST model can handle multimodal tasks, including video captioning, video question answering, video retrieval, and audio captioning by transferring all modalities - video, audio, speech, and language - into texts, which will be summarized or revised to adapt to different tasks or inputs with an LLM. Different from Vid-LLMs agents, the model is further pre-trained on the VAST-27M dataset encompassing 27 million video clips on different pre-training objectives: omni-modality video-caption contrastive/matching/generation loss. It is fine-tuned and evaluated on a wide range of datasets, including YouCook2, TVC [133], VALOR-32K [134], VATEX [135], MSR-VTT, MUSIC-AVQA, ActivityNet-QA, MSR-VTT-QA, TGIF-FrameQA, DiDeMo, Flickr [136], ClothoV1 [137], ClothoV2 [137], and AudioCap [138].

**Merlin** [90]. The model Merlin handles video understanding tasks, including object tracking, video referring, video relation, and future reasoning, by utilizing an architecture that integrates visual tokens from images and videos into language sequences for LLMs. It employs Foresight Pre-Training (FPT) and Foresight Instruction-Tuning (FIT) to model and predict object trajectories and future events from video frames. Merlin’s effectiveness was evaluated using various datasets, including LAION400M [139], Object365 [140], OpenImage [141], LaSOT [142], GOT10K [143], MOT17 [144], DanceTrack [145], SOMPT22 [146], Ref-COCO [147], VCR [148],

LLaVA-665K [149], MultiSports [150], TITAN [151], and STAR [152]. The model does not support processing sound or speech inputs.

### 3.3 Vid-LLM Instruction Tuning

In general, fine-tuning pre-trained large models is compute-intensive. Due to limited computational resources, not all parameters of the model are updated during fine-tuning of large models; instead, some parameters of adapters are updated. In Vid-LLMs instruction tuning, two types of adapters, connective and insertive, are commonly used. Some methods also mix these two types of adapters. The connective adapter is usually placed between the visual backbone and the LLM, mainly used for aligning visual and textual semantics, while the insertive adapter is typically inserted into the LLM.

#### 3.3.1 Fine-tuning with Connective Adapters

There are several types of connective adapters: linear projection layer, MLP, cross-attention layer, Q-former, and their combinations, usually used for aligning different modalities.

**Video-LLaMA** [116]. Video-LLaMA is a multi-modal framework that enhances the capabilities of LLMs in video comprehension by integrating the understanding of both visual and auditory content. This framework overcomes the challenges of capturing temporal visual changes and integrating audio-visual signals by advanced techniques such as Video/Audio Q-former [109] and imageBind [153]. In particular, Video-LLaMA consists of Vision-Language (VL) and Audio-Language (AL) branches. The VL branch employs the ViT-G/14 as its vision encoder and the BLIP-2 Q-Former as video Q-Former followed by a frame embedding layer for video encoding. The VL branch has been pre-trained on the Webvid-2M [122] and around 595K image-text pairs from LLaVA [154] and further fine-tuned with data from MiniGPT-4 [155], LLaVA [154], and VideoChat [81]. Meanwhile, the AL Branch, using a two-layer audio Q-Former and the ImageBind-Huge encoder, focuses on audio representations. Therefore, VL and AL branches enable Video-LLaMA to perceive, comprehend, and generate meaningful responses based on the rich and complex content present in videos, marking a significant advancement in the field of audio-visual language models. However, the model can handle natural sound audio as inputs but not support speech inputs.

**VALLEY** [96]. VALLEY integrates LLMs with a temporal modeling module and a visual encoder, enabling it to handle tasks such as multi-shot captions, long video descriptions, action recognition, and causal relationship inference. VALLEY processes videos by first sampling frames and extracting visual features using a pre-trained ViT-L/14 from CLIP. These features are then aggregated across time using a temporal modeling module, forming unified vision tokens. A projection layer is used to transform these visual features into the language feature space, allowing them to be processed alongside text embeddings by the LLM. The LLM backbone employs the Stable-Vicuna [111]. The model undergoes a two-stage training process. Initially, it is pre-trained using image-text and video-text pairs, incorporating data from CC3M [156] and WebVid2M datasets [122]. The second stage involves 73K self-constructed video instruction data, combined with 150K image instruction data [154] and 11K video instruction data from VideoChat [81], focusing on enhancing visual content description. VALLEY’s performance is evaluated using datasets like MSVD-QA [157], MSRVT-QA [157], ActivityNet-QA [158] for video understanding, and ScienceQA [159], MemeCap [160] for image understanding. The model does not support processing sound or speech inputs.

**Video-ChatGPT** [97]. Video-ChatGPT is a model tailored for understanding videos, specifically geared toward tasks involving spatial, temporal, and action-oriented components of video content. It models videos employing a modified CLIP ViT-L/14 visual encoder to extract spatiotemporal features, which are then aligned with language embeddings for integration into an LLM. This process allows Video-ChatGPT to input detailed video features into the LLM. Moreover, this work introduces a new dataset with 100K video instruction pairs, created through human-assisted and semi-automatic annotation methods. This dataset, which includes enriched video-caption pairs from the ActivityNet-200 dataset [161], provides the diversity and complexity needed for effective training. The semi-automatic process uses models like BLIP-2 [109] and GRiT [123] for dense captioning, further refined by GPT-assisted postprocessing by GPT-3.5. The model’s fine-tuning leverages the proposed new dataset. Regarding sound or speech inputs, Video-ChatGPT does not support these features.

**Macaw-LLM** [94]. Macaw-LLM is a multi-modal language model that handles video understanding tasks by integrating video, image, text, and audio data. It models videos by extracting features using a visual modality encoder, likely employing a framework similar to CLIP-ViT-B/16. These extracted features are then processed and aligned with textual data using a unique alignment module, making them suitable for input into the language model. For fine-tuning, Macaw-LLM uses a one-step instruction fine-tuning approach, which simplifies the adaptation process and ensures coherent alignment across modalities. The evaluation of Macaw-LLM involves datasets such as the Alpaca instruction dataset for textual instructions, COCO [162] for image instructions, and Charades and AVSD datasets for video instructions. Regarding sound or speech inputs, Macaw-LLM supports audio as part of its multi-modal approach, with audio inputs currently associated with video instruction data. The model is actively being developed to include a more focused audio instruction dataset.

**LLMVA-GEBC** [95]. The LLMVA-GEBC model, designed for Generic Event Boundary Captioning (GEBC) [163], uniquely combines advanced feature extractors with an LLM for precise video captioning. It employs CLIP-ViTG [164] with Q-former [109] and other feature extractors (i.e., CLIP [106], Omnivore [165], and VinVL [166]) to process primary and supplementary visual features. The model generates video query tokens enhanced with boundary embeddings and positional encodings. For caption generation, it utilizes an LLM, specifically OPT [167], to construct and interpret prompts, enabling accurate and contextual captioning of video events. This innovative approach has demonstrated notable success in the CVPR 2023 GEBC competition. The model does not support processing sound or speech inputs.

**mPLUG-video** [117]. The mPLUG-video model, designed for video understanding tasks, handles video category classification, video captioning, and video-text retrieval. Its approach to video modeling begins with a TimeSformer-based video encoder to extract features from sparsely sampled frames, followed by a visual abstractor module to reduce sequence length. These processed features are then input into a frozen, pre-trained Chinese GPT-3 [168] as the language decoder. For fine-tuning, mPLUG-video leverages the Youku-mPLUG dataset [117]. During evaluation, it demonstrates superior performance in video category classification and video captioning tasks. However, the model does not support processing sound or speech inputs. mPLUG-video is focused solely on visual and textual elements for video understanding, not supporting audio inputs.

**MovieChat** [101]. MovieChat primarily focuses on the processing and understanding of long videos, employing a memory mechanism based on long-short attention to extract information from extensive video content. MovieChat utilizes a frozen visual module to extract frame information from long videos using non-overlap sliding windows. Frames are sequentially placed into the short-term memory. Once the short-term memory reaches a predetermined length limit, the earliest frame token is popped and consolidated into the long-term memory. For processing long-term memory, MovieChat follows the ToMe [169] to perform a memory consolidation method, which involves using cosine similarity to assess adjacent frames and merging the most similar tokens in the neighboring frames. During inference, MovieChat can operate in a global mode, where only information from the long-term memory is fed into the LLMs for reasoning. Alternatively, in breakpoint mode, the information fed into the LLMs includes not only the long-term memory but also the current frame and the information from the current short-term memory. MovieChat’s visual module utilizes ViT-G/14 from EVA-CLIP [170], and for LLMs, it employs GPT-3.5 and Claude. Additionally, MovieChat introduces a new dataset, MovieChat-1K, for long video understanding tasks, containing 1K high-quality video clips sourced from various movies and TV series, accompanied by 14K manual annotations.

**LLaMA-VQA** [102]. LLaMA-VQA is designed for video understanding tasks in VideoQA (Video Question Answering). LLaMA-VQA addresses linguistic bias in LLMs by predicting combinations of video, question, and answer, ensuring balanced consideration of visual content and textual queries. This model is adept at temporal and causal reasoning tasks in videos. For modeling, it flips the source pair and target label within the  $\langle V, Q, A \rangle$  triplet, promoting a deeper understanding of the complex relationships in VideoQA scenarios. The model uses CLIP to encode each frame, and then uses MLPs to map the frame token into the latent space of the LLMs. It has been evaluated on five challenging VideoQA benchmarks, demonstrating superior performance to both LLM-based and non-LLM models. The model does not support for processing sound or speech inputs in the context of this model.

**Video-LLaVA** [103]. The Video-LLaVA excels in various video understanding tasks by unifying visual representations of images and videos into a single language feature space before projection. This



approach enables effective learning of multi-modal interactions, leading to significant performance improvements in video understanding. Specifically, the frozen vision encoder of LanguageBind [119] is used in the pipeline of encoding visual information, then a projection layer is used to connect the encoder of LanguageBind and LLMs. The model is trained and evaluated on mixed datasets of images and videos, demonstrating superior results across benchmarks like MSRVT, MSVD, TGIF [171], and ActivityNet. However, the model does not specifically support processing sound or speech inputs, focusing primarily on visual data.

**Chat-UniVi** [98]. The model Chat-UniVi is capable of handling various video understanding tasks such as Detail Orientation, Contextual Understanding, Temporal Understanding, and Consistency. Compared to other methods that directly send all the video information into the LLMs, Chat-UniVi models videos by employing dynamic visual tokens to represent both spatial and temporal aspects. In the visual feature encoding stage, multi-scale representation is used for LLMs to perceive both high-level semantic concepts and low-level visual details. For video understanding, it utilizes a dataset based on ActivityNet, MSRVT-QA, MSVD-QA, TGIF-QA [172], FrameQA [172], and ActivityNet-QA, and performs evaluations using the GPT-3.5 model. The model also uses image-caption pairs from datasets like COCO and CC3M-595K for training. The model does not support processing sound or speech inputs in the context of video understanding.

**AutoAD II** [99]. AutoAD II is designed for audio description (AD) tasks in movies, focusing on identifying suitable moments for AD insertion, character recognition, and AD text generation. It models video and audio by incorporating CLIP visual features, a character bank (with character names and actor images), and GPT-2 with gated cross-attention mechanisms for text generation. Key datasets used for training and evaluation include MAD (Movie Audio Description), AudioVault-AD, WebVid, and MovieNet. The model does not explicitly support sound or speech inputs but utilizes text representations derived from audio for training and evaluation. Its primary application is in enhancing the accessibility of movies for visually impaired audiences through improved AD.

**FAVOR** [118] FAVOR is a fine-grained audio-visual large language model that can process video and audio input and output text. It aligns video features, audio features, and LLM input space features using a causal Q-Former, thereby achieving a fine-grained audio-visual joint representation. The authors use the image encoder in InstructBLIP [173] and the Whisper ASR model encoder [113] to process video and audio features, respectively. Moreover, The Audio-visual Evaluation Benchmark (AVEB) has been introduced for evaluating audio-visual LLMs. This benchmark assesses the single-modal perception capabilities through a range of representative tasks, with a special emphasis on multi-modal inference. AVEB contains 6 single-modal tasks, including ASR, audio captioning (AC), image captioning (IC), optical character recognition (OCR), VQA, and Video QA, together with 5 audio-visual tasks including audio-visual speech recognition (AVSR), audio-visual scene-aware dialogue (AVSD), image spoken question answering (ISQA), audio-visual matching (AVM) and audio-visual sound source detection (AVSSD).

### 3.3.2 Fine-tuning with Insertive Adapters

Insertive adapters are usually inserted in LLMs in video instruction tuning. Compared with connective adapters, insertive adapters can better enable LLMs to generalize to new tasks.

**Otter** [104]. The Otter model is an innovative multi-modal model designed for enhanced in-context learning and instruction-following, based on the OpenFlamingo [174] framework. It utilizes the specially crafted MIMIC-IT dataset, which combines image-instruction-answer triplets with contextually related examples, fostering robust instruction comprehension. Otter is trained with a blend of pre-trained language and vision encoders, along with tunable components, amounting to approximately 1.3B trainable parameters. In particular, the Otter model adopts a LLaMA-7B [110] language encoder and a CLIP ViT-L/14 vision encoder. This model represents a significant advancement in multi-modal, in-context learning, suitable for a wide range of research and practical applications. The model does not support processing sound or speech inputs.

**VideoLLM** [105]. VideoLLM is a versatile framework that applies LLMs to a range of video understanding tasks, including Online Reasoning, Future Prediction, Memory Retrieval, and Dense Prediction. The model extracts video features using various visual encoders, such as I3D, CLIP, and SlowFast, pre-trained on datasets like ImageNet [175], Kinetics [24], and Epic-Kitchens [176]. These features are then processed through a Modality Encoder and Semantic Translator, converting them into a token sequence compatible with LLMs. For fine-tuning, VideoLLM employs three



methods: Basic Tuning, Partial Tuning, and Parameter-Efficient Fine-Tuning (PEFT) techniques like LoRA [114], Prompt Tuning, and Prefix Tuning. The model’s effectiveness is evaluated using datasets such as Epic-Kitchens, Ego4D, and others. VideoLLM does not support these inputs.

### 3.3.3 Fine-tuning with Hybrid Adapters

**VTimeLLM** [92]. VTimeLLM is a novel model designed for advanced video understanding tasks, specifically excelling in Temporal Video Grounding and Dense Video Captioning. It models videos by integrating a visual encoder (CLIP ViT-L/14) and a visual adapter into the LLM framework, converting visual information into text-like embeddings. The model undergoes a three-stage boundary-aware training process. In the first stage (feature alignment), visual features are aligned with LLM’s semantic space through image-text training; in the second stage (boundary perception), the authors transform a multi-event dataset into a QA format based on templates, aims to train VTimeLLM to possess temporal boundary awareness and understand events within the boundaries. In the third stage (instruction tuning), the authors create a dialogue dataset for instruction tuning which aims to align VTimeLLM with human intent and also enables more precise video temporal understanding. Specifically, the datasets in the three stages are LCS-558K for feature alignment, InternVid-10M-FLT [177] for boundary perception, and a combination of ActivityNet Captions [178] and DiDeMo [179] for instruction tuning in evaluation. However, VTimeLLM is not explicitly designed to process sound or speech inputs, focusing predominantly on visual and textual aspects of video understanding.

**GPT4Video** [92]. GPT4Video can handle both video understanding and generation tasks, including Video Question Answering, Video Captioning, and Text-to-Video Generation. It uses Abstractor with a cross-attention layer to condense video information along the temporal and spatial axes. as the learnable adapter, concatenating video features with temporal and spatial tokens, and fine-tunes a frozen LLaMA model via LoRA on VideoChat-11k [81] dataset for features alignment, and GPT4Video-50k dataset for instruction following and safety-alignment. For the video generation segment, GPT4Video utilizes the models from the Text-to-Video Model Gallery to generate data. The model is evaluated on the VideoQA task using MSR-VTT-QA and MSVD-QA datasets, video captioning, and text-to-video generation tasks using the MSR-VTT dataset. The model does not support audio input (natural or speech).

### 3.4 Hybrid Methods

The hybrid methods involve models that combine fine-tuning and LLM-based video agents, having the advantages of both methods simultaneously.

**VideoChat** [81]. VideoChat is an innovative chat-centric video understanding system that integrates video foundation models with large language models through a learnable neural interface. It features two main components: VideoChat-Text, which transforms video content into textual format for analysis, and VideoChat-Embed, an end-to-end model for video-based dialogue, combining video and language models for enhanced performance in spatiotemporal reasoning and causal inference. The system is fine-tuned using a specially designed video-centric instruction dataset, showcasing the significant potential for diverse video applications.

**PG-Video-LLaVA** [91]. The evaluation of PG-Video-LLaVA involves video-based generative and question-answering benchmarks, including newly introduced benchmarks specific to video object grounding. The datasets used for fine-tuning and evaluation are not specified in the abstract. This model supports the processing of sound or speech inputs by incorporating audio signals into its video understanding framework.

## 4 Tasks, Datasets, and Benchmarks

In the realm of video understanding with LLM, various tasks can be categorized as: 1. Recognition and Anticipation, 2. Captioning and Summarization, 3. Grounding and Retrieval, and 4. Question Answering.

Different tasks focus on different aspects of video understanding. Recognition and Localization lay the foundation by identifying and predicting events and actions within a video, offering a base understanding of the visual content and its potential future developments. Captioning and Description elevate this understanding by translating visual data into natural language, making videos accessible and comprehensible to a broader audience, and enhancing content discoverability. Grounding further

refines this process by establishing direct correlations between specific video elements and their textual descriptions, ensuring a precise and detailed understanding. Finally, Question Answering tackles the interactive aspect, enabling systems to respond to specific queries about video content. This could involve explaining facts found in the video or interpreting what's happening in the video itself.

## 4.1 Recognition and Anticipation

One of the fundamental lines of tasks in video understanding is to comprehend the actions and events depicted. Recognition is primarily concerned with the accurate detection and classification of actions as they occur within a video. This involves interpreting and comprehending human actions as they unfold in video sequences, thereby enabling machines to categorize these actions correctly. Example tasks include video classification, action detection, and activity recognition. Additionally, this process can be easily extended to temporal localization, which involves not only identifying specific actions but also determining their duration and sequence within the video, which will be detailed in Section 4.3.

Localization, on the other hand, delves into predicting future events or actions based on the current context derived from the video. This predictive capability is integral in dynamic environments, as it aids in forecasting potential future scenarios, thereby enhancing decision-making processes. Example tasks encompass both short-term and long-term action localization, which vary based on the duration of the sequence being predicted.

### 4.1.1 Dataset Overview

Datasets falling into this category often have labels for video segments and a predetermined, limited number of labels, which are also suitable for the retrieval tasks detailed below.

**Charades** [180]. This dataset centers on everyday household activities. It stands out due to its realistic settings and the complexity of overlapping activities in its videos.

**YouTube8M** [181]. A vast dataset comprising millions of YouTube video IDs and associated labels across diverse categories, offers a wide lens on real-world video content.

**ActivityNet** [161]. Designed for recognition, detection, and temporal localization of activities, it covers a broad spectrum of human activities with detailed temporal annotations.

**Kinetics-GEBC** [163]. An extension of the original Kinetics dataset, it provides finely annotated action segments with descriptive captions, enhancing the depth of action understanding.

**Kinetics-400** [26]. Featuring YouTube video URLs across 400 action classes, this dataset is instrumental in developing large-scale action recognition models.

### 4.1.2 Evaluation Metrics

Different metrics are employed depending on the specific task and dataset:

**Top-k Accuracy.** Utilized in single-label action recognition or single-step action localization, this metric assesses if the correct action is among the top "k" predictions. Given class imbalances, Class Mean Top-k Accuracy is often preferred for a more nuanced evaluation.

**Mean Average Precision (mAP).** Applied in multi-label recognition or multi-step prediction scenarios, where future actions are treated independently, mAP gauges the precision of predictions across various labels.

**Edit Distance (ED).** Calculating accuracy by treating predictions at each future time step independently overlooks a critical aspect: the sequential nature and importance of the order of predictions in the task, necessitating a distinct evaluation approach. Based on the Damerau-Levenshtein method, ED evaluates the order and accuracy of predicted action sequences, allowing for adjustments like insertions, deletions, or substitutions. A lower ED score indicates a closer alignment with the actual sequence, acknowledging the sequential nature of prediction tasks.

## 4.2 Captioning and Description

Moving beyond mere recognition, generating textual descriptions of video content provides a richer, more detailed understanding of video content. Such descriptions not only capture the visible elements within a single frame but also weave together the sequence of events, unraveling potential narratives or implications that unfold over time. This process often necessitates a multimodal understanding, where audio elements play a crucial role alongside visual cues to fully grasp the content’s context and meaning.

A range of tasks falls under this category, with Video Captioning standing out as a key example. This task branches into various forms, such as dense captioning, video clip captioning, and online captioning, each tackling unique facets of video interpretation.

In contrast to captioning, which provides detailed descriptions, summarization centers on distilling the core content into a succinct format. Its primary goal is to condense the essence of a video into a brief summary, with video summarization being a notable example in this domain.

### 4.2.1 Datasets Overview

Various datasets have been developed to support these tasks focusing on different aspects ranging from the depiction of human activities to the nuanced understanding of procedures knowledge. These also span a diverse array of content, encompassing everything from web-based GIFs to detailed movie descriptions.

**Microsoft Research Video Description Corpus (MSVD)** [121]. A dataset with 1,970 videos focusing on single-activity clips with multilingual captions. Each clip is accompanied by multiple crowd-sourced sentences describing the actions in the video generating brief, general descriptions of short video clips.

**Microsoft Research Video-to-Text (MSR-VTT)** [121]. This large-scale dataset consists of over 40 hours of video content, 10,000 video clips from 20 categories, and 200K clip-sentence pairs in total. This is particularly valuable for training large parameter models.

**Tumblr GIF (TGIF)** [171]. A collection of 100K animated GIFs from Tumblr, annotated with 120K sentences.

**Charades** [180]. This dataset contains videos of everyday activities indoors, captured by people across three continents, offering 27,847 video descriptions and a diverse range of scenes for video captioning challenges.

**Charades-Ego** [130]. Similar to Charades, but with 68,536 activities in 7,860 videos recorded in both first and third-person views, providing a unique perspective for activity analysis.

**ActivityNet Captions** [178]. This dataset is an extension of the original ActivityNet, tailored for recognition tasks. It features 20,000 videos, each accompanied by 100,000 detailed sentences. Its standout feature is the comprehensive coverage of each video, providing extensive annotations that are invaluable for complex video understanding and recognition tasks.

**HowTo100m** [182]. Over 100 million uncurated instructional videos, uniquely corrected for narration-video mismatch using MIL-NCE, providing a robust dataset for various video understanding tasks.

**Movie Audio Descriptions (MAD)** [183]. Comprises approximately 384K sentences and 61.4K unique words from 650 movies, focused on providing audio descriptions for the visually impaired, with minimal human intervention in post-processing.

**YouCook2** [131]. A dataset of 2,000 cooking videos from YouTube, annotated with step-by-step instructions, specifically designed for procedural understanding in the cooking domain.

**MovieNet** [184]. Offers a comprehensive collection of movie keyframes and associated metadata for movie understanding and recommendation systems research.

**Youku-mPLUG** [117]. The largest public Chinese video-language dataset, designed for video category prediction, video-text retrieval, and video captioning for Chinese-speaking audiences.

**Video Timeline Tags (ViTT)** [132]. Comprises instructional videos, each tagged with short, temporally localized descriptions, useful for video summarization and instruction generation.

**TVSum** [185]. A key benchmark dataset for video summarization, comprising 50 long videos across various genres like news and documentaries. Each video is annotated with frame-level importance scores derived from user studies, making it ideal for training models to identify and summarize crucial video segments.

**SumMe** [186]. The SumMe dataset features shorter, user-generated videos covering various activities like holidays and sports. Its focus on diverse and unstructured content, accompanied by human-created summary annotations, makes it ideal for algorithms dealing with varied video types.

**VideoXum** [187]. This dataset extended the traditional single-modal video summarization task to a cross-modal video summarization task, which involves generating visual and textual summaries with semantic coherence. VideoXum is an enriched large-scale dataset built on ActivityNet Captions. It contains 14K long videos with 140K pairs of aligned video and text summaries.

#### 4.2.2 Evaluation Metrics

The evaluation metrics in this category share similarities with scores in NLP.

**Bilingual Evaluation Understudy (BLEU).** Originally developed for machine translation, BLEU primarily focuses on lexical similarity, assessing how many words and phrases in the generated captions are present in the reference captions. It evaluates the quality of text by calculating the overlap in n-grams (word sequences of n items) between the machine-generated and reference texts.

**Metric for Evaluation of Translation with Explicit Ordering (METEOR).** METEOR, also designed for machine translation, focuses on semantic accuracy and flexible matching (beyond literal matching), considering synonyms and paraphrases, thus offering a more nuanced evaluation than BLEU. It evaluates translations based on exact, stem, synonym, and paraphrase matches between words and phrases.

**Recall-Oriented Understudy for Gisting Evaluation - Longest common subsequence (ROUGE-L).** ROUGE-L emphasizes the fluency and structure of the content by assessing the longest shared sequence of words, thus focusing on the sequence rather than individual words. It measures the longest common subsequence between the system-generated summary and a set of reference summaries, focusing on the longest co-occurring sequence of words.

**Consensus-based Image Description Evaluation (CIDEr).** Based on image captioning, CIDEr measures the similarity of generated captions to a set of reference captions by considering commonality with a consensus set of descriptions. CIDEr evaluates the relevance and specificity of captions, emphasizing terms that are more informative and distinctive to the image (or video in this case).

**Semantic Propositional Image Caption Evaluation (SPICE).** SPICE evaluates caption quality by comparing them to human references, focusing on semantic understanding and accuracy. It breaks down captions into scene graphs for a detailed assessment of their factual correctness and alignment with the image's content and actions.

**Word Mover's Distance (WMD).** WMD is a measure of the distance between text documents. It operates on the principle that similar documents have similar word distributions, assessing how much one document needs to be altered to resemble another document. In video captioning, WMD is used to evaluate how closely a generated caption resembles reference captions, focusing on the overall distribution and choice of words rather than exact sequences.

### 4.3 Grounding and Retrieval

Video grounding focuses on identifying and localizing specific moments or events in the video based on given descriptions. It encompasses a diverse array of tasks, each targeting distinct facets of the interaction between video content and textual information. Key tasks in video grounding include:

1. **Video Retrieval:** This task entails aligning video content with textual descriptions and accurately retrieving multiple instances of similar activities or moments across extensive video datasets. The challenge lies in differentiating between seemingly identical instances and ensuring the precision of retrieval based on textual cues.
2. **Temporal Localization:** The goal is to define temporal boundaries within a video that precisely correspond to a given textual description. It requires the model to interpret and

match specific video segments with the narrative or descriptive elements in the text, focusing on the temporal aspect of video content.

3. **Spatial Temporal Grounding:** This requires models to pinpoint and highlight spatial regions and temporal boundaries within videos, akin to identifying a spatial-temporal tube, that corresponds accurately to a specified text query. It involves integrating spatial awareness with the narrative context, ensuring that the identified entities align accurately with the textual descriptions provided.

#### 4.3.1 Datasets Overview

A dataset with temporal annotations is suitable for constructing retrieval and temporal grounding tasks. To create a spatial-temporal grounding task, the dataset often requires annotations such as object bounding boxes, associated semantic meanings of the objects, and their relationships within the scene.

**Epic-Kitchens-100** [188]. It is an extensive collection of first-person view videos depicting kitchen activities. This dataset is crucial for studying multi-instance retrieval and action recognition in daily kitchen scenarios, providing a unique perspective on human-object interactions.

**VCR (Visual Commonsense Reasoning)** [148]. This dataset matches images with text-based questions and answers to test models on understanding visual common sense, an important part of model interpretability and decision-making. Combining images with text-based questions and answers, it challenges models to perform well in visual common-sense understanding. This dataset is essential for assessing and enhancing model interpretability and decision-making using visual inputs.

**Ego4D-MQ and Ego4D-NLQ** [189]. As parts of the broader Ego4D project, these datasets focus on spatial and temporal grounding in first-person videos. These are essential resources for advancing research in ego-centric vision and interactive AI systems, emphasizing the subjective perspective of the camera wearer.

**Vid-STG** [190]. Tailored for spatio-temporal grounding, Vid-STG enables the development of models that can simultaneously locate and identify objects or actions both spatially and temporally within a video, representing a significant step in integrating space-time understanding in AI systems. caters to the development of models adept at spatial and temporal grounding within videos. This dataset is crucial for enhancing AI's understanding of space-time dynamics and facilitating the development of more integrated and comprehensive AI systems.

**CharadesSTA** [191]. This dataset, CharadesSTA, specializes in temporal grounding by providing annotated videos that link actions to precise time segments. It facilitates the development of advanced models for action localization, leading to more accurate and context-aware video analysis. The CharadesSTA dataset builds upon the Charades dataset by adding sentence-level temporal annotations.

**DiDeMo** [192]. DiDeMo, which stands for "Distinct Describable Moments", focuses on temporal localization in videos and emphasizes correlating specific video segments with natural language descriptions. This dataset contributes to advancing the model's ability to interpret and synchronize with temporal video content, using natural language as a bridge for understanding.

#### 4.3.2 Evaluation Metrics

The evaluation metrics for retrieval tasks bear similarity to those used in typical classification tasks, including recall and mean Average Precision (mAP), as described in Section 4.1.2.

In the context of temporal and spatial grounding, the Intersection over Union (IoU) has been adapted to measure the overlap between predicted and ground truth temporal boundaries, as well as bounding box overlap in object localization. A higher IoU indicates a closer match between the two intervals, with an IoU of 1.0 signifying an exact match. The mean IoU (mIoU) is computed as the average of the temporal IoUs across all annotations in the test set.

### 4.4 Question Answering

Adding more analytical processing to the video understanding, video question answering is a task that requires the system to answer questions about the video content. This process involves deeper

analytical processing and can be broadly categorized into two primary types: multi-choice QA and open-ended QA.

**Multi-Choice QA.** This task presents models with a series of potential answers for each question. The challenge for the models here is to accurately identify the correct answer from the given options. This approach tests the model’s ability to recognize and select the most relevant information from a set of choices.

**Open-Ended QA.** Unlike the more structured multi-choice format, open-ended QA offers a broader range of possibilities. This type can manifest in various forms, such as classification, generation, or regression, tailored to the specifics of the dataset.

Traditionally, open-ended QA has been approached as a multi-class classification task. In this setup, models classify a video-question pair into a predefined set of global answers. However, with the rising dominance of Large Language Models (LLMs) in natural language processing (NLP), there’s a shift towards treating open-ended QA as a generation task. In this modern approach, the model actively generates the answer, utilizing the video content as the contextual backdrop.

#### 4.4.1 Datasets Overview

Datasets, originally designed with detailed captions, have been repurposed for Video Question Answering (VideoQA) tasks, such as MSVD-QA, MSRVT-QA, TGIF-QA, ActivityNet-QA, Pororo-QA, and TVQA. These datasets not only differ in their video sources but also exhibit a variety in the nature of question types posed. While some datasets primarily focus on content-based questions, others require a more analytical approach that involves reasoning through the logic and narrative of the video content

**MSVD-QA [157].** Based on MSVD, this dataset was expanded by adding question-answer pairs related to the content of the videos. This change shifted the focus from caption generation to understanding and answering questions about the video content.

**MSRVT-QA [157].** MSRVT-QA is tailored for video question answering in a more controlled setting. Its strength lies in the detailed and narrative-style video descriptions, providing a rich context for QA tasks.

**TGIF-QA [172].** For TGIF-QA, the dataset was augmented with QA pairs, emphasizing temporal reasoning and understanding repetitive actions. This adaptation required creating questions for testing.

**ActivityNet-QA [158].** Originating from the ActivityNet dataset, known for its extensive library of lengthy, unedited videos. Unlike other QA datasets that may focus on shorter, more segmented content, ActivityNet-QA challenges models to grasp and interpret complex, continuous activities and storylines.

**Pororo-QA [193].** Pororo-QA is unique in its use of animated children’s stories, specifically the "Pororo the Little Penguin" series. It provides a rich narrative structure and simple language, ideal for studying story-based video understanding and question answering.

**TVQA [194].** TVQA stands out by using long-form TV show episodes, incorporating both visual and textual (subtitles and scripts) information. It offers a complex, multimodal challenge, requiring an understanding of intricate plots and character interactions over extended narratives.

#### 4.4.2 Evaluation Metrics

**Multi-Choice QA and Open-Ended QA (Classification):** The primary metric used here is accuracy. **Open-Ended QA (Generation):** For tasks where the system generates an answer, metrics commonly used in caption generation are often employed. such as BLEU, METEOR, ROUGE, and CIDEr. **WUPS (Wu and Palmer Similarity Score):** Additionally, the WUPS metric is a valuable tool for assessing answers in open-ended QA. WUPS is a softer measure of accuracy that considers synonyms and semantic similarities between words. It’s grounded in the WUP score to measure word similarity. In practice, the WUPS score offers a nuanced evaluation of the quality of generated answers by measuring word similarity based on WordNet. This metric is particularly useful in contexts where a range of semantically similar answers could be considered correct.



## 4.5 Video Instruction Tuning

This subsection addresses diverse datasets that can be used to enhance video instruction tuning for Vid-LLM models. It highlights the significance of these datasets, which range from user-annotated videos to multimodal video-text pairings, in training models for accurate interpretation and generation of video-based instructions. The variety and complexity of these datasets are essential for developing AI capabilities in areas such as AI assistants, interactive media, and robotic guidance systems, where understanding and executing video instructions is crucial.

### 4.5.1 Pretraining Datasets

To integrate vision components with the language domain, a large video-to-text dataset is often utilized. Such datasets serve as a foundation for supervised pretraining, aligning modalities without targeting specific tasks.

**VidChapters-7M** [195]. VidChapters-7M is a dataset of user-annotated video chapters with 817K videos and 7M chapters, proposed to address the issue of the understudying of the topic of segmenting long videos into chapters so that users can quickly refer to their interested content. The dataset is automatically created from online videos in a scalable manner. It involves scraping user-annotated chapters without requiring any additional manual annotation.

**VALOR-1M** [134]. VALOR-1M is a large-scale high-quality tri-modality dataset, which contains 1M audible videos with human-annotated audiovisual captions. The dataset is rich in audio concepts and audiovisual captions, making it suitable for tri-modality model pretraining and benchmarking. The VALOR-1M dataset enables the training of models that can jointly understand and generate content across vision, audio, and language modalities, leading to strong performance on various downstream tasks.

**Youku-mPLUG** [117]. Youku-mPLUG is a large-scale Chinese video-language pre-training dataset and benchmarks, containing 10 million video-text pairs for pre-training and 0.3 million videos for downstream benchmarks. The dataset is collected from Youku, a well-known Chinese video-sharing website, and is filtered for safety, diversity, and quality. Youku-mPLUG is accompanied by human-annotated benchmarks covering Cross-modal Retrieval, Video Captioning, and Video Category Classification for comprehensive evaluation of video-language models and downstream applications.

**InternVid** [177]. InternVid contains over 7 million videos totaling nearly 760,000 hours, yielding 234 million video clips accompanied by detailed descriptions totaling 4.1 billion words. Its core contribution is the development of a scalable approach to autonomously build a high-quality video-text dataset with LLMs, demonstrating its efficacy in learning video-language representation at scale.

**VAST-27M** [89]. VAST-27M is an automatically generated large-scale omni-modality video caption dataset. It comprises 27 million open-domain video clips. The dataset is designed to establish connections between multi-modality video tracks, including Vision, Audio, Subtitle, and Text. It was created by collecting 27 million open-domain video clips. Vision and audio captioners were trained separately to generate respective captions for these clips. These generated captions, along with subtitles and instructional prompts, were then integrated using an LLM to create omni-modality captions.

### 4.5.2 Fine-tuning Datasets

After aligning various modalities with the above dataset, the following datasets will encompass various subtasks and form them as video instructional tuning. To create such a dataset, various video models are used to extract textual information, which is then utilized by advanced language models like the GPT series to generate question-and-answer sequences. This process is designed to infuse reasoning abilities into video understanding models, thereby enhancing their performance in downstream tasks.

**Multi-Modal In-Context Instruction Tuning (MIMIC-IT)** This dataset contains 2.8 million multimodal in-context instruction-response pairs and 2.2 million unique instructions with multiple images or videos as input data. The dataset’s video subset includes clips from various sources such as

Ego4D, which focuses on first-person video content, and TVCaption, known for its TV series-related content.

**VideoInstruct100K** Introduced by Video-ChatGPT [97], this dataset comprises 10k high-quality video instruction pairs, primarily sourced from the ActivityNet Captions dataset. It uses various models to extract and describe visual content: BLIP-2 for frame captions, GRiT for detailed scene object descriptions, and Tag2Text for key-frame tagging. GPT-3.5 further enriches the dataset by generating question-answer pairs for four key tasks: 1. Detailed Descriptions, 2. Summarizations, 3. Creative and Generative Tasks, 4. Conversations.

## 5 Applications

Vid-LLMs have revolutionized various sectors by enabling advanced video and language processing capabilities. This section outlines their diverse applications, demonstrating the extensive and transformative impact of Vid-LLMs across industries.

### 5.1 Media and Entertainment

**Online Video Platforms and Multimedia Information Retrieval.** Vid-LLMs significantly enhance search algorithms [196], generate context-aware video recommendations [197], and aid in natural language tasks such as subtitle generation and translation [88], contributing to online video platforms and multimedia information retrieval systems. Their capabilities in analyzing videos for specific keyword retrieval [87, 198, 199] improve intelligent recommendation systems. Multimedia applications combine videos in multimedia domains like music [200].

**Video Summarization and Editing.** Vid-LLMs are integral in generating concise summaries of video content [201], analyzing visual and auditory elements to extract key features for context-aware summaries. This application is vital in news aggregation and content curation. They also contribute to the field of video editing, as covered in existing literature [73]. Besides, there also exist applications in specific domains like advertisement editing [202].

### 5.2 Interactive and User-Centric Technologies

**Virtual Education, Accessibility, and Sign Language.** Vid-LLMs serve as virtual tutors in education, analyzing instructional videos for interactive learning environments [203]. They also facilitate sign language translation into spoken language or text [204, 205], improving accessibility for the deaf and hard of hearing.

**Interactive Gaming and Virtual Environments.** In the gaming industry, Vid-LLMs play a crucial role in creating dynamic dialogues and storylines, enhancing interactive experiences with non-player characters (NPCs), and aiding in generating procedural content, such as quests and in-game texts [206, 207]. They also power customer service chatbots [208, 209]. Additionally, in AR/VR/XR, Vid-LLMs contribute to the generation of dynamic narrative content, enhancing user immersion [210, 211].

**State-Aware Human-Computer Interaction and Robot Planning.** In the field of human-computer interaction, Vid-LLMs represent a significant advancement, analyzing user videos to discern context and provide customized assistance, as highlighted in Bi et al. [86]. Interaction forms also involve video content understanding like captioning videos [212], [213]. This technology enhances user engagement in diverse applications, from education to interactive media. Concurrently, in autonomous robot navigation, the SayPlan method [214] integrates LLMs with 3D scene graphs to enable robots to interpret and navigate complex spaces in large buildings. This approach simplifies environmental complexity, plans actions, and self-corrects navigational errors, proving essential for robots operating in multi-room settings.

### 5.3 Healthcare and Security Applications

**Healthcare Innovations.** In the healthcare sector, Vid-LLMs play a crucial role in processing and interpreting medical literature, assisting in diagnostic and educational processes [215], and providing decision support for healthcare professionals. They are utilized in patient interaction tools, such as

chatbots for symptom assessment and addressing health-related queries, thereby improving patient care and access to information [216].

**Security, Surveillance, and Cybersecurity.** Vid-LLMs are crucial in security and protection, analyzing communications for potential threats [217, 218] and detecting anomalous patterns in data [219, 220]. In surveillance video analysis, they identify suspicious behaviors, aiding law enforcement [221]. Their role in cybersecurity includes identifying phishing attempts and contributing to forensic analysis by summarizing case-related texts [222].

**Advancements in Autonomous Vehicles.** In autonomous vehicles, Vid-LLMs process natural language inputs for interaction [223], assist in understanding road signs and instructions [104, 224], and improve user interfaces for vehicle control systems [223], enhancing safety and user experience.

## 6 Future Directions and Conclusion

In this survey, we have reviewed the latest advancements in video understanding with large language models (Vid-LLMs) and introduced the fundamental principles, significant discoveries, and techniques for understanding and applying Vid-LLMs effectively. We begin from the developmental history of video understanding, from traditional non-deep learning methods to neural network-based approaches, then to self-supervised pre-training for videos, and now to the current video understanding solutions based on LLMs.

### 6.1 Limitations and Future Work

Although current methods enhance the effectiveness of various downstream tasks by pre-training and fine-tuning with a large amount of video data, and the introduction of LLMs allows for a better understanding of various information in videos, there remain many challenges unresolved when facing diverse video understanding tasks in the real world.

**Fine-grained Video Understanding.** Fine-grained video understanding remains a challenge. Whether it's in the field of temporal understanding of videos or visual grounding, the lack of datasets and insufficient research has made it difficult to achieve finer granularity in video understanding tasks. Also, processing and analyzing video data requires significant computational resources. Fine-grained understanding typically means analyzing every video frame, significantly increasing the computational load. Furthermore, videos contain not just spatial information but also temporal information. Understanding how objects change and interact over time, especially at a fine-grained level, is much more complex than expected. A step further, understanding the deeper semantics of video content, such as emotions, metaphors, or the dynamics of complex scenes, is more difficult than merely recognizing objects or actions. The combination of LLMs and videos has brought a ray of hope for fine-grained video understanding. LLMs enable text to align with videos at various levels, partially addressing the issue of fine-grained video understanding.

**Long-term Video Understanding.** Since long videos contain vast amounts of frames, the extended duration of long videos adds complexity to the analysis, especially in understanding events and behaviors over time. Thus, identifying key events and maintaining attention in long videos is difficult. Effective mechanisms are needed to detect and highlight important parts, particularly in content-rich or complex plot videos.

**Multi-modal Video Understanding.** Multi-modal video understanding requires the integration of different types of data such as visual, audio, and text for a better understanding of videos. Aligning these data, especially in terms of spatial and temporal synchronization, is particularly critical. This area lacks relevant research and suffers from a scarcity of datasets. Moreover, constructing such datasets faces challenges as ensuring high quality and consistency in data annotation is often difficult. In terms of methodology, extracting and utilizing effective features across different modalities is key to achieving precise video understanding, but this process is filled with challenges.

**Human Interaction in Video Understanding.** The results of video understanding ultimately serve humans, so how to better convey human needs and understand model results is also a very important issue. The emergence of LLMs has enabled video understanding models and humans to convey information more effectively through text. However, LLMs have not completely solved the interaction problem. For example, using text to guide the model's understanding of a video cannot

handle extremely fine-grained video understanding; also, when the model outputs text, it cannot precisely describe the complex content in the video. In addition, due to the capabilities of the video encoder and LLMs, some high-level information, such as character emotions and attitudes, cannot be well represented. Therefore, how to use other prompts, such as points, scribbles, etc., to optimize the interaction between humans and video understanding models is worth studying. In addition, how to improve the video encoder’s ability to preserve details is also a major issue.

**Hallucination in Multimodal LLMs.** "Hallucination" refers to the phenomenon where the model generates responses that are significantly disconnected from the relevant source material or input. This can lead to the creation of highly erroneous or unrealistic descriptions that don’t align with the provided videos. In video understanding with LLMs, the main reasons for this situation are as follows: 1. Insufficient extraction of visual features. 2. The influence of video contextual content. 3. The domain gap between the visual feature domain and the Language domain. 4. Hallucination inherent in LLMs. Therefore, to address the impact of hallucination, solutions can be found in improving the effectiveness of video encoders, enhancing the understanding of long-term spatio-temporal contexts, and the collaboration between visual latent space and linguistic latent space.

## 6.2 Conclusion

This survey investigates the current status, limitations, and development of video understanding from three aspects: models, data, and tasks, following a chronological order. It particularly delves into the significant changes brought about by the advent of Large Language Models (LLMs) in the realm of video understanding. With the collaboration of LLMs, video understanding models are enabled to interact more effectively with humans, substantially accelerating the application and implementation of related models. Moreover, extensive video-language pre-training has notably enhanced the scalability and versatility of these models. Concurrently, Vid-LLMs are facing numerous challenges. Key issues include improving the understanding of fine-grained/long-term videos to address real-world video understanding challenges, enhancing the interaction between existing LLMs and video models for better adherence to human instructions, and resolving the hallucination issue in Vid-LLMs. These are the primary concerns that need addressing in future research. We believe this survey will serve as a vital resource for the research community and guide future studies in Vid-LLMs.

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