FunQA: Towards Surprising Video Comprehension

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https://github.com/Jingkang50/FunQA

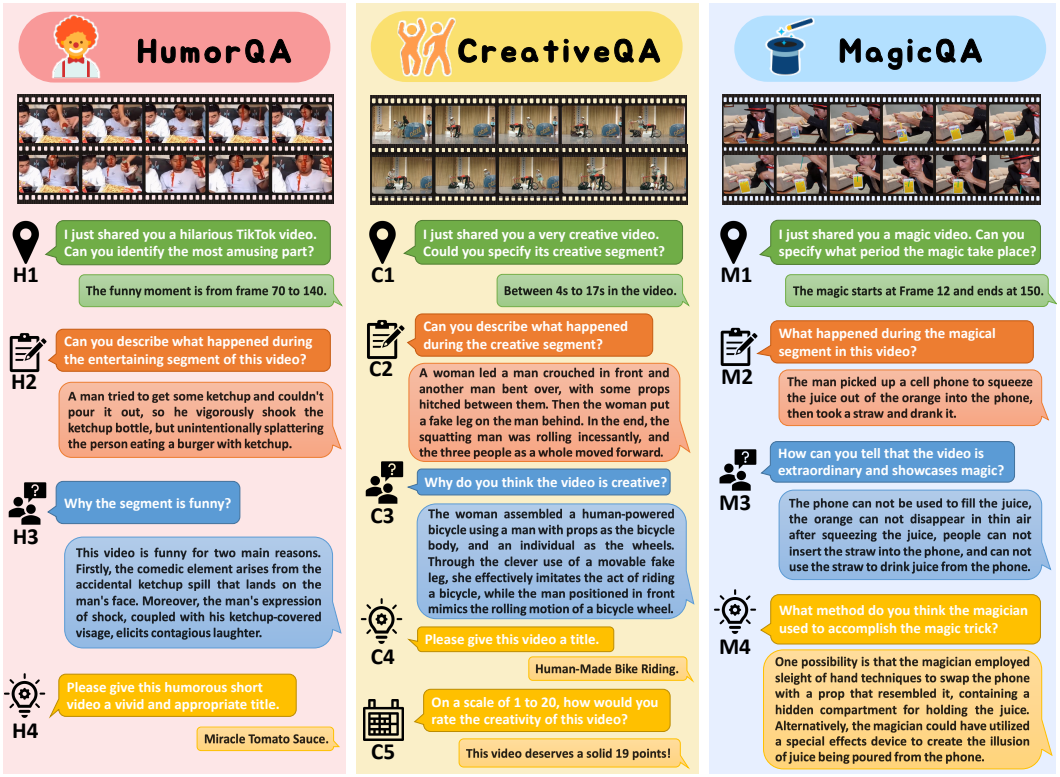

Figure 1: **Overview of FunQA.** FunQA comprises three subsets of surprising videos: *1) HumorQA, 2) CreativeQA,* and *3) MagicQA*. Each subset is associated with three common tasks: *1) counter-intuitive timestamp localization*, *2) detailed video description*, and *3) reasoning around counter-intuitiveness* (see **H1-3**, **C1-3**, and **M1-3**). Furthermore, we offer higher-level tasks tailored for each video type, such as *attributing a fitting and vivid title* for HumorQA and CreativeQA (see **H4**, **C4**), etc.

Abstract

Surprising videos, *e.g.*, funny clips, creative performances, or visual illusions, attract significant attention. Enjoyment of these videos is not simply a response to visual stimuli; rather, it hinges on the human capacity to understand (and appreciate) commonsense *violations* depicted in these videos. We introduce **FunQA**, a challenging video question answering (QA) dataset specifically designed to evalu-

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ate and enhance the depth of video reasoning based on counter-intuitive and fun videos. Unlike most video QA benchmarks which focus on less surprising contexts, e.g., cooking or instructional videos, FunQA covers three previously unexplored types of surprising videos: *1) HumorQA*, *2) CreativeQA*, and *3) MagicQA*. For each subset, we establish rigorous QA tasks designed to assess the model's capability in counter-intuitive timestamp localization, detailed video description, and reasoning around counter-intuitiveness. We also pose higher-level tasks, such as attributing a fitting and vivid title to the video, and scoring the video creativity. In total, the FunQA benchmark consists of 312K free-text QA pairs derived from 4.3K video clips, spanning a total of 24 video hours. Extensive experiments with existing VideoQA models reveal significant performance gaps for the FunQA videos across spatial-temporal reasoning, visual-centered reasoning, and free-text generation.

1 Introduction

The charm of surprising videos, be they funny, creative, or filled with visual illusions, offer enjoyment and commands attention from viewers. This type of media elicits *positive surprise* [1],[2] a captivating emotion that stems not merely from perceiving surface-level visual stimuli, but rather, the innate ability of humans to understand and find delight in unexpected and counter-intuitive moments [2]. However, despite significant advancements in today's computer vision models, the question remains: can video models "understand" the humor/creativity in surprising videos?

Consider the humorous video depicted in Figure 1 (left) as an illustrative example. We witness a man engrossed in his phone, sharing a meal with friends. Suddenly, one of his companions squeezes a generous amount of ketchup, which, instead of adorning the fries, splatters onto the man's face. The shock in his eyes, combined with his ketchup-covered visage, elicits laughter.[3] While humans effortlessly recognize this as an unusual (and potentially entertaining) event, the reasoning required to holistically understand the scene is complex: a model needs to recognize that individuals were *gathered to enjoy a meal together*, and discern that the comedic element arises from the *ketchup intended for the fries ending up on the man's face instead*, and that the innocent expression of the unfortunate victim indicates no significant harm was caused.

While there have been some efforts to enhance computer vision models' performance in Video Question Answering (VideoQA), these works have primarily focused on the common, less surprising videos found in existing VideoQA datasets. Examples of commonly employed VideoQA datasets include YouCook2 [6] which contains video clips from 2K cooking videos, Howto100M [7] which consists of only instructional videos. While there exist video datasets that explore the humor in TV shows [8, 9] and include tasks such as predicting laughter tracks [10], these tasks often heavily rely on audio and narrative cues, with visual clues might playing a lesser role.

To address this gap and evaluate computer vision models' ability to identify and understand visual commonsense violations in videos, we introduce **FunQA**, a comprehensive and high-quality VideoQA dataset comprising 4.3K surprising videos and 312K manually annotated free-text QA pairs. Our dataset consists of three subsets: *1) HumorQA*, *2) CreativeQA*, and *3) MagicQA*. Each subset covers different sources and video contents, but the commonality lies in their surprising nature, e.g., the unexpected contrasts in humorous videos, the intriguing disguises in creative videos, and the seemingly impossible performances in magic videos. Our experiments suggest that these surprising videos require different types of reasoning than common videos, as existing VideoQA methods perform poorly on the corpus. With FunQA, we hope to provide a benchmark that covers the popular, important, and sophisticated genre of counter-intuitive/surprising videos.

[2] c.f., *negative* surprise, e.g., a surprising medical bill.

[3] The hostility/superiority theory of humor posits that humor can arise from claiming superiority over someone or something [3, 4]; but alternate (more optimistic) theories of humor exist, [5] offers a survey.

Table 1: **Comparison between FunQA and other existing benchmarks.** Compare to other datasets, FunQA revolves around the captivating realm of interesting and counter-intuitive videos. The tasks within FunQA are specifically designed to challenge the vision capabilities of models, requiring strong skills in producing an in-depth description, interpretation, and spatial-temporal reasoning. Here we clarify the abbreviation in the table. **Anno.**: Annotation; **M**: Manual, **A**: Automatic; For Input, **V, A, S,** and **B** denote Video, Audio, Subtitle, and Bounding-box; **VC** means visual-centric, **Desc.** means Description, **Expl** for Explanation, **STR** for Spatial-temporal Reasoning. For QA Tasks, **MC** denotes Multiple Choice QA, **OE** means Open Ended QA, and **FT** means Free Text QA.

Datasets	Domain	Anno.	Video			Question Answer					
			Avg length (s)	# Clips (K)	Input	# QA pairs (K)	VC	Desc.	Expl.	STR	QA Task
MarioQA [11]	Games	M	3-6	188	V, A	188	Yes	No	Yes	Yes	OE
TGIF-QA [12]	Social Media	M	3.1	71.7	V	165.2	Yes	Yes	No	Yes	MC & OE
MovieQA [13]	Movies	A	202.7	6.77	V, A, S	6.4	No	No	Yes	Yes	MC
CLEVRER [14]	Synthetic Video	M	5	20	V	305	Yes	No	Yes	Yes	OE
TVQA [15]	TV shows	M	76.2	21.8	V, A	152.5	No	No	Yes	No	MC
TVQA+ [16]	TV shows	M	7.2	4.2	V, A, B	29.4	No	No	Yes	Yes	OE
Social-IQ [17]	Web videos	M	99	1.25	V, A, S, B	7.5	Yes	No	Yes	No	MC
NExT-QA [18]	Daily life	M	44	5.4	V, A	52	Yes	Yes	Yes	Yes	MC & OE
KnowIT-VQA [19]	TV shows	M	60	12	V, A, S	24	Yes	No	Yes	Yes	MC
AGQA [20]	Social Media	A	30	9.6	V, A	192	Yes	No	Yes	Yes	OE
AVQA [21]	Social Media	M	60	9.3	V, A	57.3	Yes	No	Yes	Yes	MC
STAR [22]	Daily life	A	-	22	V	60	Yes	No	No	Yes	MC
Env-QA [23]	Egocentric Video	M	20	23.3	V	85.1	Yes	No	No	Yes	MC
FIBER [24]	Daily life	M	10	28	V, A, S	2	No	Yes	No	Yes	OE
HumorQA	Daily life	M	7	1.8	V, A	141.3	Yes	Yes	Yes	Yes	OE & FT
CreativeQA	Performance	M	48	0.9	V, A	78.7	Yes	Yes	Yes	Yes	OE & FT
MagicQA	Magic	M	10	1.6	V, A	91.9	Yes	Yes	Yes	Yes	OE & FT
FunQA	**Surprising videos**	M	19	4.3	V, A	**312**	Yes	Yes	Yes	Yes	**OE & FT**

In FunQA, we formulate three rigorous tasks to measure models' understanding of surprise: *1) Counter-intuitive timestamp localization*: a model must identify the specific time period within a video when an unexpected event takes place. *2) Detailed video description*: a model must generate coherent and objective descriptions of the video content, evaluating models' fundamental video understanding capabilities. *3) Counter-intuitiveness reasoning*: a model must generate concrete explanations of why the video is surprising. These tasks progressively assess the model's ability to perceive, articulate, and reason about the counter-intuitive elements present in surprising videos. Additionally, we propose auxiliary tasks that pose higher-level challenges within the benchmark including assigning an appropriate and vivid title to the video, etc. To summarize our contributions:

1) New VideoQA Dataset: We build a large-scale dataset **FunQA**, which complements the existing VideoQA dataset with intriguing videos.

2) Novel and Challenging Tasks: We design a number of novel tasks that allow the model to explore previously untouched problems, such as timestamp localization, and reasoning around counter-intuitiveness. These tasks push video reasoning beyond superficial descriptions, demanding deeper understanding and discernment.

3) Comprehensive Evaluation: We have done an extensive and comprehensive evaluation of cutting-edge baselines, giving the field an insight and future research direction.

2 Related Work

Video Question Answering Benchmarks While the visual question answering (VQA) task focuses on enhancing models' ability in image comprehension [25, 26, 27], video question answering (VideoQA) shifts the attention towards video comprehension. VideoQA is generally more challenging than VQA as it requires a comprehensive understanding of visual content, utilization of temporal and spatial information, and exploration of relationships between recognized objects and activities [14]. To address the VideoQA task, the research community has introduced various benchmarks. As depicted in Table 1, Most commonly used VideoQA datasets are sourced from human-centric videos like movies [13], TV shows [15, 16, 19], and social media [12, 17, 18, 20, 21, 22, 24], and there are also object-centric datasets of game videos [11], synthetic videos [14] and egocentric videos [23]. MovieQA [13] and TVQA [15] are commonly employed by VideoQA methods, which put forward tasks related to temporal and causal reasoning. However, they rely heavily on dialogue comprehension

and textual plot summaries, which severely limits the challenge of visual reasoning. TGIF-QA [12] uses animated GIFs to challenge spatial-temporal reasoning, but as most GIFs are short videos of 3 seconds, and its tasks mainly focus on action description, TGIF-QA lacks complex reasoning evaluation ability. When most datasets use multiple choice questions as QA tasks, some methods, such as NExT-QA [18], try to join open-ended questions. NExT-QA mainly focuses on daily life videos, but the open-ended answers are mostly simple sentences containing only a few words. To sum up, most existing methods focus on ordinary videos, lack of understanding of intriguing or unexpected videos, and advanced reasoning tasks such as generating complete explanatory texts of videos remain to be explored.

Video Question Answering Solutions Earlier studies have explored various models, including LSTMs and graph-based neural networks, to capture cross-modal information [28, 29]. With the advent of Transformers, video understanding models like ClipBERT [30] and CoMVT [31] emerged, focusing on the comprehension of specific frames within a video. Subsequent models, such as Violet [32], extended their ability to encompass temporal and spatial information. However, these methods have primarily been applied to short videos. In the realm of long videos, MIST [33] stands out by achieving state-of-the-art performance and excelling in terms of computation efficiency and interpretability. Furthermore, recent Vision Language Models (VLMs) such as [34, 35, 36] have showcased remarkable video understanding capabilities.

Counter-Intuitive Benchmarks While many current computer vision benchmarks primarily focus on understanding commonsense content, there is a growing interest in addressing the realm of counter-intuitiveness. Several emerging benchmarks and models cater to this domain, such as Whoops [37], which emphasizes weird, unusual, and uncanny images, and MemeGraphs [38], which revolves around memes featuring humor and sarcasm. Furthermore, some work even challenges models to comprehend complex multimodal humor in comics [39]. In the realm of large vision-language models, exemplified by GPT-4 [40], there is a particular focus on showcasing their ability to provide explanations for funny pictures. However, when it comes to videos, existing datasets exploring humor in TV shows or comedy tend to heavily rely on audio and narrative cues [8, 9, 10], with visual clues playing a comparatively lesser role.

3 FunQA Dataset

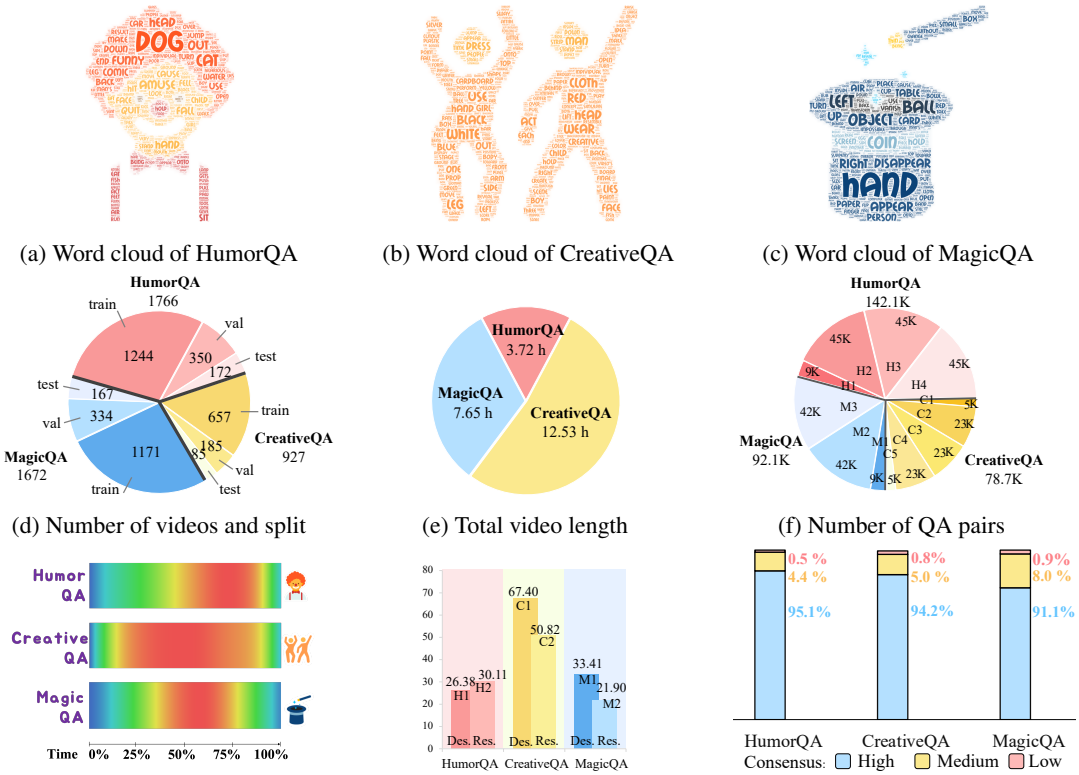
In this section, we provide a detailed explanation of the design principles that guided the creation of the FunQA dataset and its subsets. Additionally, we introduce our novel VideoQA tasks tailored for FunQA, and FunQA data statistics in Figure 2. We introduce our construction pipeline in the end.

3.1 Video Selection

In constructing the dataset, we adhered to three principles to address the challenges in video understanding capabilities: our dataset, FunQA, is **visual centered** and emphasizes **counter-intuitive reasoning**, **spatial-temporal reasoning**. Based on these principles, we collect 4365 videos from 3 different art genres and created three subsets: HumorQA, CreativeQA, and MagicQA.

HumorQA HumorQA composed of 1,769 meticulously curated web videos, serves as a unique source of insight into human humor comprehension. Notably, it contains the shortest average video length of 7s among the three subsets. We believe that the human process of understanding humor is complex and deep, requiring a holistic understanding of the video and adding a degree of common sense to it. Psychological research has demonstrated that humor arises from the incongruity [41, 42] between reality and expectations, flourishing with the skillful juxtaposition and transformation of events [43, 44, 45]. This makes humorous videos a valuable asset for the VideoQA dataset, anticipated to enhance a model's proficiency in integrating information and performing deep reasoning.

CreativeQA CreativeQA is a collection of 927 videos averaging 48s in length from a TV show called Kasou Taishou [46]. This program, showcasing original and novel skits performed by various amateur groups and judged by a panel, boasts a strong creative flair [47]. The essence of the show lies in using a mix of people and props to mimic reality, with audiences deriving pleasure from information integration and comparison. We anticipate that the imitation nature of the show will



(a) Word cloud of HumorQA (b) Word cloud of CreativeQA (c) Word cloud of MagicQA

(d) Number of videos and split (e) Total video length (f) Number of QA pairs

(g) Time Dist. of localization task (h) Avg. word count of answers (i) Anno. consensus evaluation

Figure 2: **Statistics of FunQA Dataset.** FunQA consists of three subsets, each corresponding to different video types, and is annotated with free-text QA pairs. The first row displays word clouds representing critical annotations for each subset. The second row provides key dataset statistics, including the number of videos for different splits, video length, and QA pair count for three subsets. In the last row, (g) highlights the high-frequency time span of the answer for localization questions in red, (h) shows the average word count of answers, and (i) presents the percentage of consensus between annotators for the same answer in a sampled set.

challenge the model's capacity for information extraction, while the longer video length and need for understanding creativity will put to test the model's comprehension of spatial-temporal information.

MagicQA MagicQA encapsulates 1672 magic performance videos sourced from across the web, spanning various genres like camera magic, close-up magic, and stage magic. The essence of magic revolves around the creation of seemingly impossible illusions [48], employing diverse effects such as disappearance, creation, and transformation. These illusions are infused with abundant spatial-temporal information. Through this dataset, we aim to empower the model to not only track the ensuing changes in objects but also unravel the underlying mechanics [49] of these transformations.

3.2 Task Definition

To comprehensively evaluate the model's ability to understand surprising videos, we designed the following 4 types of tasks for each subset:

Counter-intuitive Timestamp Localization Task The localization task is the base task to assess the model's comprehension abilities. It involves localizing counter-intuitive segments within the video, answers expressed in either seconds or frames. This task serves as the basis for the subsequent two main tasks in the three subsets, where the focus shifts to locating moments of humor, creativity, and magical effects, respectively. Successfully completing this task demands the model's understanding of the video's overall content, incorporating both temporal and spatial information.

Detailed Description Task The description task aims to evaluate the model's information extraction capabilities, serving as a fundamental aspect of video understanding. Across all three subsets, this

task requires providing a free-text answer that describes the selected moment. Furthermore, this task allows for analysis of how the model extracts information and generates answers for subsequent tasks. By examining the model's performance in this task, we gain insights into its ability to extract relevant information and generate meaningful responses.

Counter-intuitiveness Reasoning Task The reasoning task is designed to test the model's ability to reason about the video, and in the three subsets, this question is Why Humorous, Why creative, and Why counter-intuitive and the answer is a free-text explanation. This task is very difficult and involves the model's deep reasoning ability; it requires the model to give a complete explanation using information from the entire video and its own common sense.

Higher Level Tasks In addition to the three main tasks, we design higher-level tasks to enhance the model's inference abilities on counter-intuitive videos. *Title Task* in HumorQA and CreativeQA requires generating a concise title summarizing the video's content. *Creative Scoring Task* in CreativeQA involves rating the creativity of videos between 0 and 20. *Magic Method Task* in MagicQA requires the model to explain clearly the rationale behind the magic, and its purpose is to test the model's ability to reason more deeply. To ensure the accuracy of the answers, this task is only partially annotated and appears only in the test set, details of which can be found in Appendix A.1.

In addition, some visual QA benchmarks [37] have begun to adopt free-text answers; this flexible answer format enables multimodal LLMs to go beyond multiple choice options (Large Language Models) [35, 36]; for Video QA, however, free-text are less common. To bridge this gap, we also consider some **free-text answer** evaluations, demanding enhanced video comprehension capabilities from the model. It will also assess the model's ability to generate reasonably lengthy textual responses.

3.3 Dataset Statistics

FunQA contains **4,365** counter-intuitive video clips and **311,950** question-answer pairs, the total length of these videos is **23.9h** and the average length of video clips is **19** seconds. FunQA consists of three fine-grained subsets, each one containing well-designed tasks. The specific numbers and split of videos can be seen in Figure 2 (d). Each subset's video lengths can be seen in Figure 2 (d). The specific number of QA pairs for each task can be seen in Figure 2 (e).

For our localization task, the timestamp heat map for the three different types of videos can be seen in Figure 2 (g), which shows the high-frequency time span of the answer. For the description and reasoning tasks, the average length of the words in their free-text answers reached **34.24**, which is much longer than existing VideoQA datasets (e.g., 8.7 in Activity-QA [50], 11.6 in NExT-QA [18]). The specific word count of each task is shown in Figure 2 (h). FunQA has a well-established annotation process and high annotation quality, the result of our annotation consensus evaluation can be seen in Figure 2 (i). For each video category, more than 90% of the annotations exhibit a high level of consensus, with only 1% of the content showing low consensus. Approximately 8% of the data demonstrates variations in consensus, thus highlighting the objectivity of our dataset.

HumorQA, CreativeQA, and MagicQA word clouds are shown in Figure 2 (a-c). More statistics and FunQA full word cloud are given in Appendix A.3.

3.4 Dataset Construction Pipeline

FunQA dataset construction pipeline was in three stages: Pre-processing, Manual Annotation, and Post-Processing. The whole process took about 900 hours with over 50 highly educated undergraduates as part-time annotators, and we paid crowd-workers a target of ¥25/hr. More details of the dataset construction pipeline can be seen in Appendix A.1.

Pre-processing Initially, we crawled videos from TikTok, Bilibili, and YouTube (these videos are a collection of surprising videos). Then we performed a two-stage manual cleaning and cutting process on the collected videos to ensure counter-intuitive features and video quality and to exclude non-ethical content and sensitive information, resulting in a cut video clip.

Manual Annotation We annotated the videos according to the characteristics of different tasks design in Chinese. We screen and train the annotators to ensure the accuracy and high quality of the annotation, and finally produce the original annotated files. After the first round of annotation, we

conducted a secondary annotation of 10% of the tasks and performed Consensus Evaluation to ensure the objectivity of our annotations.

Post-processing Based on our carefully designed tasks and high-quality annotations, we expanded our dataset using GPT-3.5. Firstly, we automatically translated the Chinese annotations into English. Subsequently, we generated more QA pairs that were faithful to the original ideas but presented differently. This not only made FunQA multilingual but also increased the number of QA pairs to 312K. Additionally, we created diverse task types, such as FunQA multiple-choice and FunQA dialogue. More details are given in Appendix A.2 and Appendix B.

4 Experiments

In this section, we present an introduction to caption-based and instruction-based models, followed by an exploration of diverse metrics for evaluating FunQA tasks. Our comprehensive experiments and deep analysis of the results are then presented. More details are given in Appendix C.2.

4.1 Baselines

4.1.1 Caption-based Models

mPLUG mPLUG [51] consists of two unimodal encoders for image and text independently, a cross-modal skip-connected network, and a decoder for text generation. Based on the connected representation of the image and prefix sub-sequence, the decoder is trained with a prefix language modeling loss by generating the remaining caption.

GIT GIT [52] is composed of one image encoder and one text decoder, for videos, multiple frames are sampled and encoded independently, and features are added with an extra learnable temporal embedding before concatenation. The image encoder is based on the contrastive pre-trained model [53] with raw image input and a compact 2D feature map output. The text decoder is a transformer module to predict the text description.

4.1.2 Instruction-based Models

VideoChat VideoChat [35] is an end-to-end chat-centric video understanding system, the version we use is VideoChat-13B. Its VideoChat-Embed architecture is instantiated using BLIP-2 [54] and StableVicuna (13b-delta), and combines pre-trained ViT-G [55] and GMHRA [56]. For the token interface, VideoChat-Embed uses the pre-trained QFormer with an additional linear projection to output Video Embedding. Both video description and Video Embedding will be input in LLMs (LLAMA-13B [57]) for multimodal understanding and output timestamped video text descriptions.

Video-ChatGPT Video-ChatGPT [36] is a large vision-language model with a dedicated video-encoder and LLM, which feeds the video frames into pre-trained video encoder, adds spatio-temporal features and feeds them into linear layer. Video Embedding is then input into LLM (Vicuna-7B, v1.1) along with System command and User Query to output the answer. It uses a data-centric, human-assisted, and semi-automated annotation framework for high-quality video instructional data with unique multimodal (visual-verbal) capabilities.

Otter The Otter model [34] utilizes the OpenFlamingo training paradigm, where the pretrained OpenFlamingo model consists of a LLaMA-7B language encoder [57] and a CLIP ViT-L/14 vision encoder [58]. In the fine-tuning process for instruction tuning, Otter freezes both the encoders and only fine-tunes the Perceiver resampler module. We evaluate two versions of Otter: one that is fine-tuned on the Dense Caption dataset [59], and another that is fine-tuned on the FunQA training set. Due to GPU memory limitations, Otter can only train and test on 128 frames from a video.

4.2 Evaluation Metrics

Timestamp Localization (H1, C1, M1) We employ the intersection of union based on time span.

Description & Reasoning (H2-4, C2-4, M2-3) For all the **free-text** tasks, we employ three approaches for evaluation. Firstly, we utilize traditional NLG(Natural Language Generation) metrics.

Table 2: **Main Results on FunQA Benchmark.** The FunQA benchmark consists of four task categories. H1, C1, M1 represent the counter-intuitive timestamp localization task, where **IOU** is used as the metric. H2, C2, M2 represent the detailed video description task, and H3, C3, M3 represent reasoning around counter-intuitiveness. For the higher-level tasks, H4, C4 involve attributing a fitting and vivid title. The responses for all these tasks in free-text format. We use the following metrics: **BLEU-4 / ROUGE-L / CIDEr** (shown in the first row) and **BLEURT / GPT-4** (shown in the second row) for evaluation. C5 represents scoring the video creativity, and the metric is the **Difference** between the predicted score and the official score. We tested the caption-based and instruction-based models. Here we clarify the abbreviation in the table. **L.M.**: GIT_LARGE_MSRVTT; **L.V.**: GIT_LARGE_VATEX; **D.C.** means finetuned on Dense Caption; **FunQA** means finetuned on FunQA.

	HumorQA				CreativeQA					MagicQA		
	H1	H2	H3	H4	C1	C2	C3	C4	C5	M1	M2	M3
- Caption-based Model												
mPLUG [47]	-	**1.5** / 16.4 / **1.0** 19.9 / 16.0	1.1 / 12.5 / 0.4 25.7 / 18.1	0.6 / 7.5 / 0.1 22.1 / 17.3	-	0.4 / 13.4 / 0.0 14.9 / **24.3**	0.7 / 12.6 / 0.1 24.2 / 9.0	0.3 / **3.2** / 0.0 **20.8** / 13.7	-	-	**1.2** / 15.8 / **0.5** 19.7 / 16.9	0.9 / 8.9 / 0.4 21.2 / 8.8
GIT (L.M.) [52]	-	0.5 / 12.8 / 0.2 22.4 / 22.0	-	**1.1** / 7.7 / **0.7** 17.0 / 26.8	-	0.0 / 6.4 / 0.0 14.4 / 5.0	-	0.3 / 1.5 / 0.2 7.1 / 25.2	-	-	0.2 / 11.2 / 0.1 19.4 / 12.7	-
GIT (L.V.) [52]	-	1.2 / **16.9** / 0.6 33.3 / 31.5	-	1.0 / **8.8** / **0.7** **25.9** / 33.2	-	0.1 / 8.3 / 0.0 20.5 / 5.0	-	**0.5** / 2.8 / **0.4** 10.5 / 23.3	-	-	0.6 / 13.7 / 0.1 29.8 / **21.4**	-
- Instruction-based Model												
VideoChat [35]	-	0.5 / 13.7 / 0.0 **44.0** / **37.9**	0.5 / 13.5 / 0.0 **45.4** / 31.9	0.8 / 5.1 / 0.5 20.2 / **61.7**	-	0.3 / 7.5 / 0.0 21.7 / 10.9	0.3 / 7.7 / 0.0 22.8 / 27.7	0.2 / 1.2 / 0.2 7.3 / **51.1**	67.5	-	0.6 / 15.5 / 0.0 47.4 / 14.2	0.3 / 9.2 / 0.0 43.1 / 24.6
Video-ChatGPT [36]	-	0.5 / 14.0 / 0.1 39.9 / 20.7	0.7 / 12.4 / 0.1 40.1 / **33.0**	0.4 / 3.2 / 0.2 18.6 / 47.5	-	**1.1** / **19.8** / **0.2** **45.8** / 19.1	0.8 / 17.3 / 0.1 **45.2** / **30.1**	0.2 / 1.9 / 0.2 18.8 / 44.5	**85.4**	-	0.7 / **20.8** / 0.0 **50.0** / 11.8	0.5 / 11.3 / 0.0 **43.3** / **29.2**
Otter (D.C.) [34]	-	1.1 / 14.3 / 0.4 30.2 / 9.8	1.2 / 14.2 / 0.4 32.3 / 13.9	0.5 / 5.4 / 0.1 21.7 / 13.3	-	0.5 / 13.8 / 0.1 28.7 / 11.0	1.0 / 16.8 / **0.2** 32.9 / 10.6	0.3 / 2.3 / 0.1 17.7 / 4.2	45.0	-	1.0 / 15.0 / 0.3 32.5 / 14.4	1.1 / 12.8 / 0.2 27.3 / 13.7
Otter (FunQA) [34]	-	1.3 / 16.7 / 0.5 33.7 / 12.2	**1.3** / **14.4** / **0.5** 37.4 / 21.0	0.6 / 3.6 / 0.2 24.6 / 20.0	-	0.6 / 15.8 / 0.1 33.1 / 11.9	**2.0** / **20.2** / **0.2** 36.8 / 21.1	0.3 / 1.5 / 0.2 18.1 / 23.9	69.4	-	1.1 / 17.3 / 0.3 40.0 / 18.4	**2.2** / **15.4** / **0.8** 38.0 / 19.8

We use BLEU-4 [60], ROUGE-L [61], CIDEr [62], and BLEURT [63] as our metrics. The first two rely on N-gram overlap, which is only sensitive to lexical variations and cannot identify changes in sentence semantics or grammar. The latter two are reference-based evaluation metrics. Secondly, several works [64, 65, 66, 67] have shown promising results in utilizing GPT as a metric for NLG. Therefore, we introduce GPT-4 to assist in evaluating free-text similarity. We carefully design the prompts to make it possible to give objective ratings as much as possible like a human being. More details of GPT-4 prompts and evaluation criteria are provided in Appendix C.1.

Creative Scoring (C5) The evaluation uses the formula: $Metrics = 100 \times \left(1 - \frac{|Predict - GT|}{20}\right)$.

4.3 Results and Observations

Our results are summarized in Table 2. As an illustration, the responses of different models on HumorQA can be seen in Figure 3. Overall, the performance of the models on the FunQA dataset is generally unsatisfactory, and we have made several key findings:

Timestamp localization task is the most challenging. Caption-based models, due to their emphasis on captioning tasks, tend to provide descriptions of the entire video even when tasked with timestamp localization (refer to Appendix C.3). Conversely, instruction-based models, which are typically derived from image-based VLMs, focus on specific keyframes rather than considering the entire temporal space of the video.

No clear winner across all tasks. Caption-based models excel in providing detailed descriptions but struggle in tasks that require reasoning, resulting in a notable performance gap between description tasks (e.g., H2) and reasoning tasks (e.g., H3). On the other hand, instruction-based models demonstrate stronger reasoning capabilities but tend to underperform in description tasks. One possible explanation is that instruction-based models may generate excessive information in their answers, including a significant amount of incorrect information.

Performance varies greatly across different video types. Most models can get a relatively accurate answer in humor and magic videos but have difficulty answering the questions in creative videos. One possible reason is that humor and magic videos often depict daily life that models have

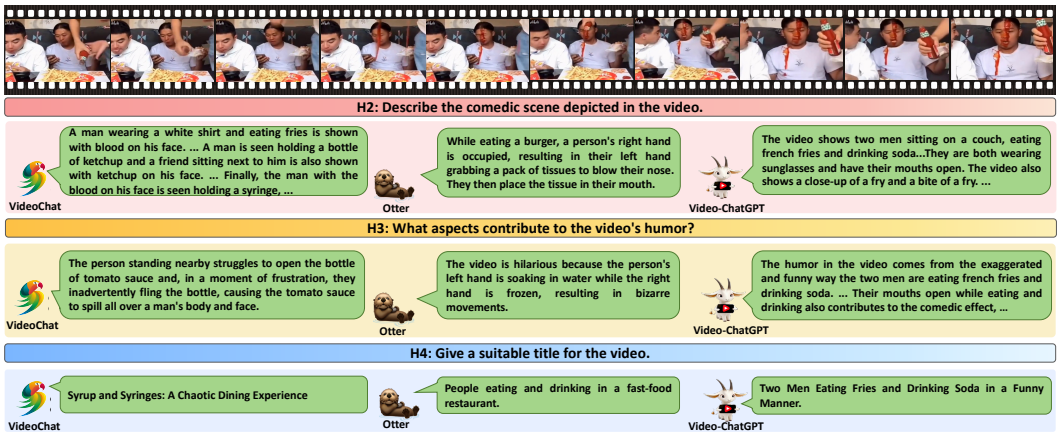


Figure 3: **Model responses on a HumorQA example.** Here shows the answers given by VideoChat [35], Video-ChatGPT [36], and Otter [34] on HumorQA video in Figure 1. On task **H2**, **H3**, VideoChat has the best performance. On task **H4**, Video-ChatGPT and Otter answer better, which is in line with our experiment result in Table 2. However, the answers from all models are still far from the ground truth. The descriptions of details and counter-intuitive explanations have numerous shortcomings. For example, Video-ChatGPT added incorrect details to the description, such as "wearing sunglasses", the humorous reason for "throwing ketchup" was wrongly interpreted by VideoChat as "knocking over the ketchup bottle", etc.

encountered previously, whereas creative videos contain content that models have never seen before, rendering them unable to generate new ideas and resulting in irrelevant and erroneous answers.

Insufficient evaluation metrics for free-text tasks. Traditional metrics yield near-zero scores on free-text questions, as they solely focus on short textual similarity. While BLEURT scores are significantly higher, they still fall short in evaluating more complex similarities. Intuitively, GPT-4 is found to show preliminary capabilities in assessing free-text in deep understanding, which will be detailed in Appendix C.3. However, there are still issues of instability, where the same content can receive different scores.

Fintuned Otter performs well on traditional metrics but lags behind in GPT-4 score. We finetuned Otter on Dense Caption and FunQA, and Otter (FunQA) shows obvious performance advantages over Otter (D.C.). While Otter performs better in traditional metrics like ROUGE-L compared with other instruction-based models, the GPT-4 score of Otter (FunQA) underperforms. One possible reason revealed is that the input of Otter is only 128 frames sampled from the video, which is insufficient for comprehensive reasoning. Besides, the discrepancy between Otter's scores on traditional metrics and GPT-4 matches our finding of the lack of evaluation metrics.

5 Limitations and Future Work

This paper has two limitations. **1)** Current FunQA dataset mainly includes video-level data and annotations, but denser annotations can be developed to explore more possibilities of video reasoning. Examples include detailed spatial and temporal annotations, such as captions corresponding with specific time axes and annotations of object level. **2)** The raw annotations are completed by the annotator in Chinese. In the process of translating into English, we first use GPT to polish and supplement Chinese annotations, making the text as thorough as possible, as short or incomplete text may result in misunderstanding. However, there may still be differences due to cultural diversities between the two languages.

In the future, we expect to expand our dataset with denser and more diverse annotations. Also, new metrics will be explored to better evaluate models' performance, especially in open-ended questions which lack in-depth metrics. Finally, we hope to provide directions for advancing models toward deeper video reasoning. Specific ideas include that Otter can sample more frames from the input video to improve causal reasoning capacity.

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References

[1] Marret K Noordewier and Seger M Breugelmans. On the valence of surprise. *Cognition & emotion*, 27(7):1326–1334, 2013. 2

[2] Mike W Martin. Humour and aesthetic enjoyment of incongruities. *The British Journal of Aesthetics*, 23(1):74–85, 1983. 2

[3] Charles R Gruner. *Understanding laughter: The workings of wit & humor*. Burnham Incorporated Pub, 1978. 2

[4] Michael Billig. *Laughter and ridicule: Towards a social critique of humour*. Sage, 2005. 2

[5] Salvatore Attardo. A primer for the linguistics of humor. *The primer of humor research*, 8:101–156, 2008. 2

[6] Luowei Zhou, Chenliang Xu, and Jason Corso. Towards automatic learning of procedures from web instructional videos. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018. 2

[7] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2630–2640, 2019. 2

[8] Santiago Castro, Devamanyu Hazarika, Verónica Pérez-Rosas, Roger Zimmermann, Rada Mihalcea, and Soujanya Poria. Towards multimodal sarcasm detection (an _obviously_ perfect paper). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Florence, Italy, 7 2019. Association for Computational Linguistics. 2, 4

[9] Md Kamrul Hasan, Wasifur Rahman, AmirAli Bagher Zadeh, Jianyuan Zhong, Md Iftekhar Tanveer, Louis-Philippe Morency, and Mohammed (Ehsan) Hoque. UR-FUNNY: A multimodal language dataset for understanding humor. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2046–2056, Hong Kong, China, November 2019. Association for Computational Linguistics. 2, 4

[10] Badri N. Patro, Mayank Lunayach, Deepankar Srivastava, Sarvesh, Hunar Singh, and Vinay P. Namboodiri. Multimodal humor dataset: Predicting laughter tracks for sitcoms. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pages 576–585, January 2021. 2, 4

[11] Jonghwan Mun, Paul Hongsuck Seo, Ilchae Jung, and Bohyung Han. Marioqa: Answering questions by watching gameplay videos. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2867–2875, 2017. 3

[12] Yunseok Jang, Yale Song, Chris Dongjoo Kim, Youngjae Yu, Youngjin Kim, and Gunhee Kim. Video Question Answering with Spatio-Temporal Reasoning. *IJCV*, 2019. 3, 4

[13] Makarand Tapaswi, Yukun Zhu, Rainer Stiefelhagen, Antonio Torralba, Raquel Urtasun, and Sanja Fidler. Movieqa: Understanding stories in movies through question-answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4631–4640, 2016. 3

[14] Kexin Yi, Chuang Gan, Yunzhu Li, Pushmeet Kohli, Jiajun Wu, Antonio Torralba, and Joshua B. Tenenbaum. Clevrer: Collision events for video representation and reasoning, 2020. 3

[15] Jie Lei, Licheng Yu, Mohit Bansal, and Tamara L Berg. Tvqa: Localized, compositional video question answering. In *EMNLP*, 2018. 3

[16] Jie Lei, Licheng Yu, Tamara L Berg, and Mohit Bansal. Tvqa+: Spatio-temporal grounding for video question answering. In *Tech Report, arXiv*, 2019. 3

[17] Amir Zadeh, Michael Chan, Paul Pu Liang, Edmund Tong, and Louis-Philippe Morency. Social-iq: A question answering benchmark for artificial social intelligence. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8807–8817, 2019. 3

[18] Junbin Xiao, Xindi Shang, Angela Yao, and Tat-Seng Chua. Next-qa:next phase of question-answering to explaining temporal actions, 2021. 3, 4, 6

[19] Noa Garcia, Mayu Otani, Chenhui Chu, and Yuta Nakashima. Knowit vqa: Answering knowledge-based questions about videos. In *Proceedings of the Thirty-Fourth AAAI Conference on Artificial Intelligence*, 2020. 3

[20] Madeleine Grunde-McLaughlin, Ranjay Krishna, and Maneesh Agrawala. Agqa: A benchmark for compositional spatio-temporal reasoning, 2021. 3

[21] Pinci Yang, Xin Wang, Xuguang Duan, Hong Chen, Runze Hou, Cong Jin, and Wenwu Zhu. Avqa: A dataset for audio-visual question answering on videos. In *Proceedings of the 30th ACM International Conference on Multimedia*, pages 3480–3491, 2022. 3

[22] Bo Wu, Shoubin Yu, Zhenfang Chen, Joshua B. Tenenbaum, and Chuang Gan. STAR: A benchmark for situated reasoning in real-world videos. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021. 3

[23] Difei Gao, Ruiping Wang, Ziyi Bai, and Xilin Chen. Env-qa: A video question answering benchmark for comprehensive understanding of dynamic environments. pages 1675–1685, October 2021. 3

[24] Santiago Castro, Ruoyao Wang, Pingxuan Huang, Ian Stewart, Oana Ignat, Nan Liu, Jonathan C. Stroud, and Rada Mihalcea. Fiber: Fill-in-the-blanks as a challenging video understanding evaluation framework, 2022. 3

[25] Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering, 2017. 3

[26] Yuke Zhu, Oliver Groth, Michael Bernstein, and Li Fei-Fei. Visual7w: Grounded question answering in images, 2016. 3

[27] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A. Shamma, Michael S. Bernstein, and Fei-Fei Li. Visual genome: Connecting language and vision using crowdsourced dense image annotations, 2016. 3

[28] Xiangpeng Li, Jingkuan Song, Lianli Gao, Xianglong Liu, Wenbing Huang, Xiangnan He, and Chuang Gan. Beyond rnns: Positional self-attention with co-attention for video question answering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 8658–8665, 2019. 4

[29] Zhou Zhao, Zhu Zhang, Shuwen Xiao, Zhou Yu, Jun Yu, Deng Cai, Fei Wu, and Yueting Zhuang. Open-ended long-form video question answering via adaptive hierarchical reinforced networks. In *IJCAI*, volume 2, page 8, 2018. 4

[30] Jie Lei, Linjie Li, Luowei Zhou, Zhe Gan, Tamara L Berg, Mohit Bansal, and Jingjing Liu. Less is more: Clipbert for video-and-language learning via sparse sampling–supplementary file. 4

[31] Paul Hongsuck Seo, Arsha Nagrani, and Cordelia Schmid. Look before you speak: Visually contextualized utterances. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16877–16887, 2021. 4

[32] Tsu-Jui Fu, Linjie Li, Zhe Gan, Kevin Lin, William Yang Wang, Lijuan Wang, and Zicheng Liu. Violet: End-to-end video-language transformers with masked visual-token modeling. *arXiv preprint arXiv:2111.12681*, 2021. 4

[33] Difei Gao, Luowei Zhou, Lei Ji, Linchao Zhu, Yi Yang, and Mike Zheng Shou. Mist: Multi-modal iterative spatial-temporal transformer for long-form video question answering. *arXiv preprint arXiv:2212.09522*, 2022. 4

[34] Bo Li, Yuanhan Zhang, Liangyu Chen, Jinghao Wang, Jingkang Yang, and Ziwei Liu. Otter: A multi-modal model with in-context instruction tuning. *arXiv preprint arXiv:2305.03726*, 2023. 4, 7, 8, 9

[35] Kunchang Li, Yinan He, Yi Wang, Yizhuo Li, Wenhai Wang, Ping Luo, Yali Wang, Limin Wang, and Yu Qiao. Videochat: Chat-centric video understanding. *arXiv preprint arXiv:2305.06355*, 2023. 4, 6, 7, 8, 9

[36] Salman Khan Muhammad Maaz, Hanoona Rasheed and Fahad Khan. Video-chatgpt. https://github.com/mbzuai-oryx/Video-ChatGPT, 2023. 4, 6, 7, 8, 9

[37] Nitzan Bitton-Guetta, Yonatan Bitton, Jack Hessel, Ludwig Schmidt, Yuval Elovici, Gabriel Stanovsky, and Roy Schwartz. Breaking common sense: Whoops! a vision-and-language benchmark of synthetic and compositional images, 2023. 4, 6

[38] Vasiliki Kougia, Simon Fetzel, Thomas Kirchmair, Erion Çano, Sina Moayed Baharlou, Sahand Sharifzadeh, and Benjamin Roth. Memegraphs: Linking memes to knowledge graphs, 2023. 4

[39] Jack Hessel, Ana Marasović, Jena D. Hwang, Lillian Lee, Jeff Da, Rowan Zellers, Robert Mankoff, and Yejin Choi. Do androids laugh at electric sheep? humor "understanding" benchmarks from the new yorker caption contest, 2022. 4

[40] OpenAI. Gpt-4 technical report, 2023. 4

[41] Immanuel Kant. *Critique of judgment*. Hackett Publishing, 1987. 4

[42] John Morreall. Philosophy of Humor. In Edward N. Zalta and Uri Nodelman, editors, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, Summer 2023 edition, 2023. 4

[43] Robert L Latta. *The basic humor process: A cognitive-shift theory and the case against incongruity*. De Gruyter Mouton, 1999. 4

[44] Brian Boyd. Laughter and literature: A play theory of humor. *Philosophy and literature*, 28(1):1–22, 2004. 4

[45] Arthur Koestler. The act of creation. In *Brain Function, Volume IV: Brain Function and Learning*, pages 327–346. University of California Press, 2020. 4

[46] Nippon Television Network Corporation. Kasou taishou. https://www.ntv.co.jp/kasoh/index.html. [Accessed 23-Apr-2023]. 4

[47] Mark A Runco and Garrett J Jaeger. The standard definition of creativity. *CREATIVITY RESEARCH JOURNAL*, 24(1):92–96, 2012. 4, 8

[48] Henning Nelms. *Magic and showmanship: A handbook for conjurers*. Courier Corporation, 2012. 5

[49] Peter Lamont and Richard Wiseman. *Magic in theory: An introduction to the theoretical and psychological elements of conjuring*. Univ of Hertfordshire Press, 2005. 5

[50] Zhou Yu, Dejing Xu, Jun Yu, Ting Yu, Zhou Zhao, Yueting Zhuang, and Dacheng Tao. Activitynet-qa: A dataset for understanding complex web videos via question answering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 9127–9134, 2019. 6

[51] Chenliang Li, Haiyang Xu, Junfeng Tian, Wei Wang, Ming Yan, Bin Bi, Jiabo Ye, Hehong Chen, Guohai Xu, Zheng Cao, Ji Zhang, Songfang Huang, Fei Huang, Jingren Zhou, and Luo Si. mplug: Effective and efficient vision-language learning by cross-modal skip-connections, 2022. 7

[52] Jianfeng Wang, Zhengyuan Yang, Xiaowei Hu, Linjie Li, Kevin Lin, Zhe Gan, Zicheng Liu, Ce Liu, and Lijuan Wang. Git: A generative image-to-text transformer for vision and language. *arXiv preprint arXiv:2205.14100*, 2022. 7, 8

[53] Lu Yuan, Dongdong Chen, Yi-Ling Chen, Noel Codella, Xiyang Dai, Jianfeng Gao, Houdong Hu, Xuedong Huang, Boxin Li, Chunyuan Li, Ce Liu, Mengchen Liu, Zicheng Liu, Yumao Lu, Yu Shi, Lijuan Wang, Jianfeng Wang, Bin Xiao, Zhen Xiao, Jianwei Yang, Michael Zeng, Luowei Zhou, and Pengchuan Zhang. Florence: A new foundation model for computer vision, 2021. 7

[54] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models, 2023. 7

[55] Quan Sun, Yuxin Fang, Ledell Wu, Xinlong Wang, and Yue Cao. Eva-clip: Improved training techniques for clip at scale, 2023. 7

[56] Yi Wang, Kunchang Li, Yizhuo Li, Yinan He, Bingkun Huang, Zhiyu Zhao, Hongjie Zhang, Jilan Xu, Yi Liu, Zun Wang, Sen Xing, Guo Chen, Junting Pan, Jiashuo Yu, Yali Wang, Limin Wang, and Yu Qiao. Internvideo: General video foundation models via generative and discriminative learning, 2022. 7

[57] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023. 7

[58] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision, 2021. 7

[59] Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles. Dense-captioning events in videos. In *Proceedings of the IEEE international conference on computer vision*, pages 706–715, 2017. 7

[60] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318, 2002. 8

[61] Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81, 2004. 8

[62] Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575, 2015. 8

[63] Amy Pu, Hyung Won Chung, Ankur P Parikh, Sebastian Gehrmann, and Thibault Sellam. Learning compact metrics for mt. In *Proceedings of EMNLP*, 2021. 8

[64] Jiaan Wang, Yunlong Liang, Fandong Meng, Haoxiang Shi, Zhixu Li, Jinan Xu, Jianfeng Qu, and Jie Zhou. Is chatgpt a good nlg evaluator? a preliminary study. *arXiv preprint arXiv:2303.04048*, 2023. 8

[65] Jinlan Fu, See-Kiong Ng, Zhengbao Jiang, and Pengfei Liu. Gptscore: Evaluate as you desire. *arXiv preprint arXiv:2302.04166*, 2023. 8

[66] Ehsan Kamalloo, Nouha Dziri, Charles LA Clarke, and Davood Rafiei. Evaluating open-domain question answering in the era of large language models. *arXiv preprint arXiv:2305.06984*, 2023. 8

[67] Cheng-Han Chiang and Hung-yi Lee. Can large language models be an alternative to human evaluations? *arXiv preprint arXiv:2305.01937*, 2023. 8

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] We build a large-scale dataset with novel and challenging tasks to comprehensively benchmark surprising videoQA answering.
   (b) Did you describe the limitations of your work? [Yes] See Limitation and Future Work
   (c) Did you discuss any potential negative societal impacts of your work? [No] We cannot find any potential negative societal impacts in our work
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] We read it and our dataset does not contain sensitive items
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] https://github.com/Jingkang50/FunQA
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Method & Experiment and Appendix C.2
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] We have no error bars
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix C.2
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes] We submitted a request to the video copyright owner and cite the models used. See Appendix A.1
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] We provide the codebase link
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] We have applied for copyright on any video. See Appendix A.1
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] We respect the personally idntifiable in the video such as the right to be portrayed, which is the responsibility of the copyright owner.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes] We show the annotation instru
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [Yes] We pay part-timers 25¥ per hour for a total of 900 hours for a total of approximately 22,500¥. See in Section 3.4