

# NEPTUNE: THE LONG ORBIT TO BENCHMARKING LONG VIDEO UNDERSTANDING

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## ABSTRACT

This paper describes a semi-automatic pipeline to generate challenging question-answer-decoy sets for understanding long videos. Many existing video datasets and models are focused on short clips (10s-30s). While some long video datasets do exist, they can often be solved by powerful image models applied per frame (and often to very few frames) in a video, and are usually manually annotated at high cost. In order to mitigate both these problems, we propose a scalable dataset creation pipeline which leverages large models (VLMs and LLMs), to automatically generate dense, time-aligned video captions, as well as tough question answer decoy sets for video segments (up to 15 minutes in length). Our dataset Neptune covers a broad range of long video reasoning abilities and consists of a subset that emphasizes multimodal reasoning. Since existing metrics for open-ended question answering are either rule-based or may rely on proprietary models, we provide a new open source model-based metric (GEM) to score open-ended responses on Neptune. Benchmark evaluations reveal that current open-source long video models perform poorly on Neptune, particularly on questions testing temporal ordering, counting and state changes. Through Neptune, we aim to spur the development of more advanced models capable of understanding long videos.

## 1 INTRODUCTION

Videos are experiencing an *explosion* moment online, with new research constantly pushing the frontier for video and language tasks such as video question answering (VideoQA) (Xu et al., 2017; Zhong et al., 2022; Xiao et al., 2021; Yang et al., 2021; Mangalam et al., 2023). Early video and language models, while adept at VideoQA, have largely focused on short, trimmed clips (less than 1 minute long (Yu et al., 2019a; Xiao et al., 2021)). The recent release of powerful, longer context multimodal models (eg. Gemini 1.5 (Reid et al., 2024) and GPT4 (Achiam et al., 2023)), however, has ushered in the promise of models being able to reason over millions of tokens, covering longer stretches of videos (many minutes long).

While promising, these claims are often evidenced by qualitative examples, or results on small-size datasets – for example the 1H-VideoQA (Reid et al., 2024) benchmark, which while valuable, only consists of 125 questions. Popular video benchmarks for question answering still tend to focus on short, trimmed clips (*e.g.*, Next-QA (Xiao et al., 2021)). Other datasets that *do* contain longer videos are often ‘short-term’ benchmarks disguised as long-term ones, evidenced by models that are able to solve them with a single (or a few) frames (*e.g.* some tasks on the LVU dataset (Wu & Krahenbuhl, 2021) such as scene prediction of movies). Other long video datasets may contain strong linguistic biases in multiple choice evaluation, as shown by MoreVQA (Min et al., 2024), which gets strong performance on EgoSchema (Mangalam et al., 2023) without access to the video at all, or can be solved with external internet knowledge, such as those made from popular movies (Li et al., 2023d).

A key challenge in creating a truly long form video understanding dataset is the significant manual cost required to select, watch, understand and annotate long videos with free-form natural language.

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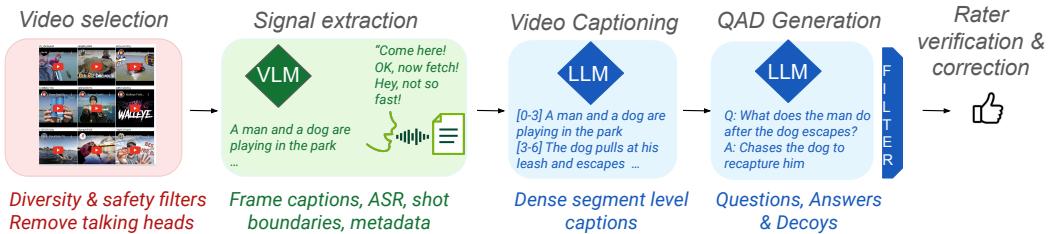


Figure 1: **Pipeline Overview:** Our pipeline consists of 5 key stages - (i) Video selection, where suitable videos are identified from YouTube, (ii) Signal extraction, (iii) Video level captioning, (iv) Question, answer and decoy (QAD) generation and (v) Manual rater verification. The first four stages are entirely automatic. Before rater verification, we automatically filter out QADs that can be solved by an LLM without access to the video content.

Answering challenging questions about longer videos is often a *multimodal* (as it may involve listening to the audio track in addition to watching the video), and *non-sequential* endeavour (as sometimes it is necessary to rewind and rewatch key parts to answer a question). Proposing suitable high-level questions that are not trivially solved by a few frames is also tricky for humans to do consistently and with adequate diversity. The key aim of this paper is to solve this challenge by leveraging automatic tools to reduce rater effort while at the same retaining quality. Inspired by EgoSchema, we do this by proposing a scalable dataset creation pipeline (Fig. 1) that leverages strong foundational Video Language Models (VLMs) and Large Language Models (LLMs) with carefully designed prompts. We first generate dense, time-aligned video captions automatically, from which tough question-answer-decoy (QAD) sets can be automatically derived. This is done by extracting image captions, automatic speech recognition (ASR), shot boundaries and video metadata, and combining these signals with multi-stage, chain of thought prompting of an LLM. Our pipeline can be applied to any video on YouTube (Fig. 1).

While most of the pipeline is automatic, a comprehensive rater verification stage at the end ensures quality. While other dataset pipelines that are entirely manual (Zhou et al., 2024; Fang et al., 2024; Wang et al., 2024), our verification stage is lightweight, which we show by ablating the automatic part of the pipeline, and measuring the time taken by raters to propose QAs for videos from scratch. Results show that our semi-automatic pipeline almost halves rater effort. Our dataset is called Neptune<sup>1</sup>, and covers a diverse range of videos, is multimodal (requires audio and visual information), and poses challenging questions for videos that test a variety of reasoning abilities over long time horizons. Neptune allows for two modes of evaluation: multiple-choice and open-ended question answering. Since existing metrics for open-ended question answering are either rule-based and derived from captioning (WUPS (Wu & Palmer, 1994), CIDEr (Vedantam et al., 2015), etc) or are LLM-based evals that rely on proprietary APIs (such as ChatGPT<sup>2</sup>), we finetune an open source model on a generic answer equivalence dataset (Bulian et al., 2022) to score question answering results and evaluate it as a metric on a manually annotated answer equivalence dev set. We call this new metric Gemma Equivalence Metric (GEM).

To summarise, we make the following contributions: (i) We propose a scalable pipeline to generate complex QAD annotations for any video that halves rater time compared to manual annotation. (ii) We use this pipeline to generate the Neptune evaluation-only dataset, which consists of 3,268 QAD annotations for 2,405 videos. We also release a *challenging* subset, NEPTUNE-MMH for which *vision* plays an important role. (iii) We provide both multiple choice and open-ended evaluation metrics. For the latter, we propose a new open-ended metric called Gemma Equivalence Metric (GEM) which outperforms rule-based metrics on a manually annotated answer equivalence dataset; and finally (iv) We provide benchmarking and ablations of state-of-the-art VideoQA models on the Neptune sets. Benchmarking shows a significant gap between open-source video models and proprietary models such as Gemini-1.5 and GPT-4. All data will be released publicly to the research community.

<sup>1</sup>Named after the planet with the longest orbit

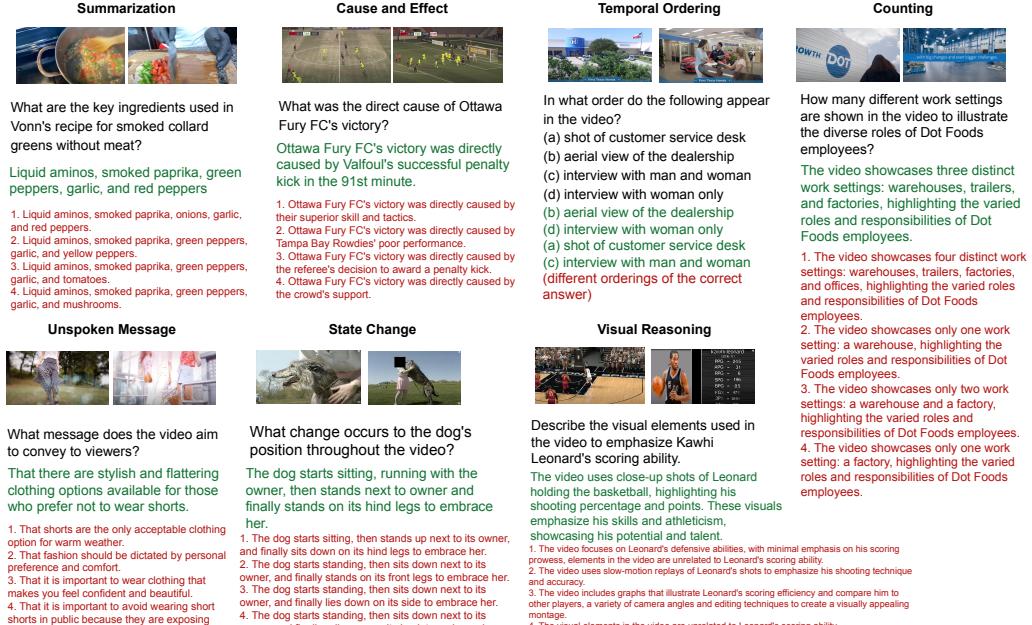
<sup>2</sup><https://openai.com/index/chatgpt/>

## 2 RELATED WORKS

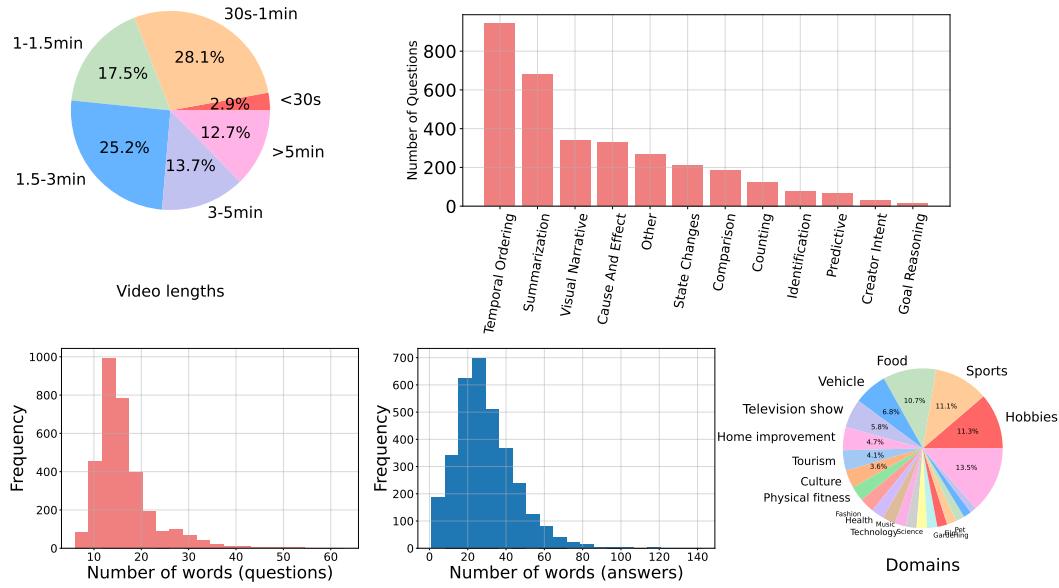
**Video Question Answering:** Video Question-Answering (VideoQA) is an important task for assessing multimodal video understanding systems’ ability to reason about videos (Xu et al., 2017; Zhong et al., 2022; Xiao et al., 2021; Yang et al., 2021; Mangalam et al., 2023). Vision and language models for this task can be broadly classified into three categories: (i) early end-to-end VLMs for this task which typically consists of strong vision and language encoders/decoders, such as Flamingo (Alayrac et al., 2022), BLIP2 (Li et al., 2023b), Video-Llama (Zhang et al., 2023a), GIT2 (Wang et al., 2022) and PALI (Chen et al., 2022; 2023a;b). These typically are moderate sized models, and memory limits often lead to significant downsampling: *e.g.* temporally sampling a few frames with large strides (Wang et al., 2022; Chen et al., 2023a) or spatially subsampling each frame to a single token (Yang et al., 2023; Zhou et al., 2018; Wang et al., 2021); (ii) Socratic style models (Zeng et al., 2022), which consists of combining various specialised *frozen* models with carefully prompted state-of-the-art VLMs and LLMs (eg. MoreVQA (Min et al., 2024)) and (iii) end-to-end large multimodal models such as Gemini (Gemini Team Google, 2023) and GPT-4 (Achiam et al., 2023), which have long context lengths and can ingest multimodal data, including video, sound and text.

**Video QA Benchmarks:** Key datasets have pushed towards assessing reasoning for temporal questions (Grunde-McLaughlin et al., 2021; Xiao et al., 2021; Wu et al., 2021), longer videos (Yu et al., 2019a; Mangalam et al., 2023), as well as focusing on diverse domains like instructional (Yang et al., 2021) and egocentric videos (Gao et al., 2021; Mangalam et al., 2023). We summarise existing VideoQA benchmarks in a table provided in the appendix. Most datasets either focus on shorter videos (less than 100s), or are short video datasets ‘in disguise’, and can actually be solved with a few frames (*e.g.* ActivityNet-QA (Yu et al., 2019b) or MovieQA (Tapaswi et al., 2016)). 1H-VideoQA (Reid et al., 2024) consists of videos longer than 1 hour, but is limited to 125 questions and is closed-source. Like Neptune, ActivityNet-RTL (Huang et al., 2024), CinePile (Rawal et al., 2024) and EgoSchema (Mangalam et al., 2023) are generated by prompting LLMs, but cover only limited domains and rely on existing annotations while Neptune covers a much broader spectrum of video types and its pipeline is applicable to arbitrary videos. Most importantly, EgoSchema also has strong linguistic biases, while Neptune mitigates these through filtering (Sec. 5). Unlike other benchmarks which come with their own training sets (eg. MSR-VTT (Xu et al., 2016), ActivityNet (Yu et al., 2019a)), we propose a generalisation-focused *zero-shot* evaluation regime. The goal for Neptune is to benchmark any model, pre-trained with any external dataset or task, in order to assess real-world domain transfer. Hence we release *test* sets only. More discussion on related datasets and dataset pipelines is provided in the appendix.

**Metrics for open-ended VideoQA:** Earlier QA datasets consisted of short answers (Xiao et al., 2021) (sometimes a single word), typically from a closed set, and therefore metrics such as accuracy or accuracy with exact match (EM) can be applied. As datasets have evolved with more real-world annotation (longer, open-set answers), designing a metric becomes challenging. Existing rule-based metrics for captioning, such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and CIDEr (Vedantam et al., 2015) can be applied, however they all primarily measure n-gram overlap, and do not capture the inherent subjectivity of the task, where different phrasing is often equally valid. Other metrics for captioning include SPICE (Anderson et al., 2016) (adds action and object relationships), while model-based metrics using earlier language models or image-language models include BERT-Score (Zhang et al., 2020), BERT-Score++ (Yi et al., 2020) (fine-tunes BERT for image captioning), LEIC (Cui et al., 2018), NUBIA (Kane et al., 2020), TIGER (Jiang et al., 2019), CLIPScore (Hessel et al., 2021), and EMScore (Shi et al., 2022). For answer equivalence specifically, token F1 and exact match (EM) have been used, but suffer many of the same shortcomings that rule-based metrics do, and EM is often too strict for open-ended eval. BEM (Bulian et al., 2022) finetunes BERT on an answer-equivalence dataset, and shows that this provides a better score for QA. Recently, LLMs trained with reinforcement learning from human feedback (RLHF) that already exhibit strong human alignment (Bubeck et al., 2023) are used in works such as VideoChatGPT (Maaz et al., 2023) and MovieChat (Song et al., 2023) (LLM-as-a-judge). A challenge here is that the models used (ChatGPT) are called via proprietary APIs, where the underlying model may be non-static, thereby leading to non-reproducibility in the metric. Instead, we take a state-of-the-art open-sourced lightweight language model (Team et al., 2024a) and finetune it on a public answer equivalence dataset (Bulian et al., 2022), to create an open-source, static, model-based evaluation metric.



**Figure 2: Examples from Neptune:** We show examples from the dataset that highlight key question types from our dataset. We show 2 frames from each video. Correct answer is provided in green and decoys are shown in red. Best viewed zoomed in and in colour. Some decoys are summarised for brevity.



**Figure 3: Neptune Statistics:** We show the distribution of video lengths (top, left), the number of questions per question type (top, right), the distribution question and answer lengths (bottom, left and middle) and the domains in Neptune (bottom, right). Note that greater than 12% of the videos are longer than 5 minutes (305) and over 25% are longer than 3 minutes. An expanded plot of the video domains is provided in the appendix.

### 3 NEPTUNE

In this section we describe our dataset generated by the pipeline described in Sec. 4. We first discuss motivating principles, which affect much of the prompt design in the pipeline stage (Sec. 4). Each video contains one or more annotation sets, which consists of a question, an answer to the question and four decoys (which are used for multiple choice evaluation). Our key motivation is that

questions should not be answerable by: (i) looking at a single (or few) frames; (ii) using text-only LLMs alone (language, common sense) that have no access to the video; (iii) with only the video’s speech transcript, and (iv) questions should cover a number of high-level ‘question types’, which are discussed next and described in more detail in the appendix.

**Question Types.** Neptune covers a broad range of long video reasoning abilities, which are provided as ‘question type’ labels for each question. Examples are provided in Fig. 2, and the distribution of questions per question type is depicted in Fig. 3 (right). More information about the distribution of question types is provided in the appendix. Question types are obtained by carefully prompting an LLM (described in Sec. 4.3) and include *Video Summarisation*, which involves summarising and comparing long parts of the video, as well as identifying the most important segments of the video; *Visual Reasoning*, which involves understanding visual elements, as well as reasoning about why visual content is used (e.g. to convey a certain mood); *Temporal Ordering*, including the timeline of events; *State Changes*; *Counting* of higher level instances; *Cause and Effect*, and understanding the *Unspoken Message* or *Creator Intent* in a video.

**Dataset Statistics.** Our dataset consists of **3,268** questions from **2,405** videos, covering **100** hours of video. We truncate videos longer than 15 minutes, with the smallest video being 16 seconds and the average length of videos being 2.5 minutes. We show the distribution of video lengths in Fig. 3 (top, left). Note that greater than 12% of the videos are longer than 5 minutes (305 videos) and over 25% are longer than 3 minutes, which is the maximum length of videos in the EgoSchema dataset. The distribution of questions per question type is depicted in Fig. 3 (top, right). The most frequent question type is Temporal Ordering, followed by Summarization. Questions are on average 16.3 words long, while answers and decoys are 29.5 and 29.0 words long respectively. A full distribution of lengths can be seen in Fig. 3 (bottom, left). We also note that the videos in Neptune cover a diverse range of topics (Fig. 3 – bottom, right), an expanded version of this plot is provided in the appendix.

## 4 DATASET CREATION PIPELINE

An overview of our pipeline can be found in Fig. 1. In order to reduce human effort, we leverage automatic tools to (i) find suitable videos (ii) extract useful signals and then (iii) automatically generate video level captions and QADs. We then send the data to human raters for the final manual verification stages. Our pipeline can be applied to any generic YouTube video. This is unlike existing data pipelines such as those used to create EgoSchema (Mangalam et al., 2023), which relies on human generated captions, SFD (Ghermi et al., 2024) and other movie related datasets, which requires movie titles, loglines and synopses (human-written), or MLVU (Zhou et al., 2024), which re-uses annotations from existing datasets for many of their tasks. This makes the dataset scalable, as YouTube has a constantly growing set of videos. Each stage is described in detail below.

### 4.1 VIDEO SELECTION AND SIGNAL EXTRACTION

**Video Selection:** We begin with the YT-Temporal-1Bn (Zellers et al., 2022a) dataset. Because this dataset has strong speech and visual alignment, it consists of a lot of videos where ‘*talking heads*’ dominate the screen (eg. VLOGs, product placements, etc). We attempt to reduce the number of such videos in order to capture more interesting scenes, objects and actions. This is done by extracting face detections with frontal gaze where face bounding-box height is greater than 20%, and removing videos where more than 30% of frames have such frontal gaze. We then apply safety filters to remove racy, local controversy content etc, as well as applying filters to maximise semantic and person diversity. Details about these processes are provided in the appendix.

**Signal Extraction:** For each video we extract the following signals: (i) *Frame captions*: A visual description of each frame (extracted at 1fps) is obtained from PaLI-3 (Chen et al., 2023b). (ii) *ASR*: the speech is transcribed using the YouTube API; (iii) *Metadata*: We obtain the YouTube title and the description for each video; and (iv) *Shot boundaries* for each video.

### 4.2 AUTOMATIC VIDEO CAPTIONING

The signals described above (frame captions, ASR, title and description, shot boundaries) are automatically combined to create video-level captions in a multi-stage process. Examples of caption quality are provided in the appendix, showcasing details such as visual elements, multiple events, mood and atmosphere, details from the ASR, and even high level feelings and emotions. Video captions are obtained using the following steps:

**Shot Visual Captions:** Using the shot boundaries, the *frame captions* are summarized into shot-level descriptions (*shot captions*) by prompting the same LLM. We then create a script for each video

containing the shot timestamps, the shot visual captions and the ASR transcript.

**Topic and Description Pairs:** If ASR exists, an initial list of structured topics for the video (along with a short topic description) is formed by prompting an LLM with the ASR (see appendix). Note that this already yields decent topics as the initial list of videos have been selected (by the YT-Temporal-1Bn authors) to have a strong correlation between ASR and visual content.

**Shot Clustering:** Shots are then clustered per-video using an LLM prompted with the semantic topics obtained above. In each cluster, there may be one or many shots that correspond to that topic. A diagram on this stage and the exact prompt used is provided in the appendix.

**Segment Captions:** Consecutive shots of the same topic are then merged as one segment. Shots of the same topic that are not contiguous are treated as separate segments (see appendix for an example). We then generate dense captions for each segment using a custom prompt (see appendix).

**Adding Visual Support:** To extract a better visual description of the segment that will be used for QA generation in the next phase, an extra step is performed to get visual support for each segment. That visual support is stored separately in conjunction with the dense caption for the segment. For this purpose, the dense caption from the previous step is used alongside the shot level visual captions. The LLM prompt used is provided in the appendix, and the the LLM used for all the above steps is Gemini-1.0-Pro ([Gemini Team Google, 2023](#)).

#### 4.3 QAD (QUESTION-ANSWER-DECOY) GENERATION

We automatically generate questions, answers and decoys (QADs) by feeding the video captions from above to custom prompted LLMs. Our prompts are inspired by the EgoSchema dataset pipeline ([Mangalam et al., 2023](#)), with key modifications to generate more visually focused questions, as well as to generate questions belonging to a set of different question types. The exact prompts used are provided in the appendix. We generate QADs in two stages: (i) Given the video captions from the previous step, we first generate questions and answers; (ii) in the second stage we generate six decoys given the questions and answers from the previous stage. We found this 2-stage method to work better empirically than generating the QADs all in one go.

#### 4.4 LLM-BASED BLIND FILTER

**QAD filter:** LLM-based generation can sometimes yield QAD triplets that can be answered from common sense or external world knowledge without the video as context. In particular, we observed that LLMs are often capable of inferring the correct answer from subtle cues in the answer candidates, for example if the correct answer is a positive sentiment while the decoys are negative. To remove such questions, we apply an LLM-based blind filter. We prompt an LLM (Gemini-1.0-pro) to rank the answer candidates to a question. To avoid false rejections due to random correct guesses, we repeat this process three times and only filter out questions where the model predicted the correct answer at least two times out of three (this number was selected to maximise number of videos left given the accuracy trade-off and is discussed in the appendix). Chain-of-thought reasoning improves accuracy so we ask the model to provide a rationale alongside its ranking.

#### 4.5 MANUAL RATER VERIFICATION

The final stage involves manual human verification. Raters are first asked to rate the quality of the question based on 4 criteria (details in the appendix). If the question is not suitable, the entire QAD set is discarded. If the question is accepted, raters annotate which modalities are required to answer the question. Choices are: “audio+video”, “video-only”, or “audio-only”. Next, raters are asked to either accept the answer as-is or modify it. Decoys are annotated in a final stage. Given the six LLM-generated decoy candidates, raters verify that they are actually incorrect answers to the question and select the four most challenging ones. If less than four decoys are suitable, we provide a text field for raters to write their own decoys. Screenshots of the rater UI are provided in the appendix. We noticed that rater corrections reintroduce a small amount of questions that can be answered without context, so as a final step we repeat the QAD filter described above. We applied two rounds of manual rater verification to improve dataset quality. More details about rater training, replication (multiple raters per question) and pipelining are provided in the appendix.

**Human Proposed Questions.** To test the effectiveness and efficiency of the automatic portion of our dataset pipeline, we asked raters to propose questions and answers entirely manually for a subset of the dataset. We call this set HPQ (Human Proposed Questions). The raters are provided with a few examples of each question type before they begin annotating. In total, we collect 270 QAs for 193 videos in this set. We use this set in two ways - (i) to quantitatively measure rater-time saved by our

Table 1: Evaluation of open-ended metrics on the GEM answer equivalence dev set.  
FT: Fine-tuning

Metric	FT data	F1-Score
CIDEr (Vedantam et al., 2015)	None	56.4
ROUGE-L (Lin, 2004)	None	62.2
BEM (Bulian et al., 2022)	BEM	61.5
Gemma-2B-IT (Team et al., 2024a)	None	56.3
Gemma-7B-IT	None	65.2
Gemma-9B-IT (Team et al., 2024b)	None	70.3
Gemma-9B-IT (GEM)	BEM	71.2
Gemini-1.5-pro (Reid et al., 2024)	None	<b>72.8</b>

Table 2: Results on the Human Proposed Question (HPQ) Split. \*Results on NEPTUNE-FULL are reported on a subset containing the same set of videos as HPQ.

Method	Frames	ASR	FULL*	HPQ
Video-LLaMA-2	16	No	13.04	14.18
MovieChat	150	No	2.49	1.97
MiniGPT4-Video	45	No	5.14	4.10
Gemini 1.5 Pro	all	Yes	45.05	44.44
Gemini 1.5 Pro	all	No	27.67	24.81

automatic pipeline, and (ii) to estimate the amount of Gemini bias in our semi-automatic pipeline. The results for both are provided in Sec. 5.3.

## 5 EXPERIMENTS

We first introduce the two sets in Neptune and our evaluation metrics and then present evaluations using both baseline and state-of-the-art models.

### 5.1 NEPTUNE SETS AND EVALUATION METRICS

**Neptune Sets:** Because we seeded our dataset from the YT-Temporal-1Bn (Zellers et al., 2022b) videos, we note that it contains some videos where ASR can play a big role in contributing to the video content. In order to create a more challenging *visual* benchmark, we also provide Neptune-MMH (multimodal human annotated), where we identify videos where vision should play an important role. This is created by using the rater annotations for what modalities are required to answer the question (described in Sec. 4.5), and discarding questions which the raters marked can be solved by audio-only, and consists of 1,171 QADs for 1,000 videos. We encourage the community to evaluate on this *harder* subset as well.

**Evaluation:** We explore two different protocols for evaluation of question answering - multiple choice evaluation (which involves selecting the correct answer amidst 4 decoys), and open-ended evaluation, which involves producing an answer directly without any decoys and assessing answer quality directly. While the former has the advantage of easier metrics (simple accuracy), the latter removes any potential confounding biases in the decoys. In the next section, we outline our process for creating a new open-ended metric called GEM.

**Gemma Equivalence Metric (GEM):** As discussed in Sec. 2, existing metrics for open-ended QA either lack robustness or rely on proprietary LLM APIs that can change over time. We therefore aim to produce a static open-ended metric. Towards this, we first manually construct a labelled dev-set with 292 (question, reference answer, candidate answer) triplets, with equivalence scores between 0 and 1. See appendix for details on the construction of the dev set. We then benchmark a number of rule-based and model-based metrics on this set in Table 1. To demonstrate the two ends of the scale, we first note that rule-based metrics such as CIDEr (Vedantam et al., 2015) and ROUGE-L (Lin, 2004) obtain F1-Scores of 56.4 and 62.2, while an LLM-based metric using Gemini-1.5-pro (Reid et al., 2024) gets an F1-Score of 72.8 (but is closed-source). Next, we apply static open-source lightweight language models, namely the Gemma family of models i.e. Gemma-2B (Team et al., 2024a), Gemma-7B (Team et al., 2024a) and Gemma-9B (Team et al., 2024b) to judge the answers in a zero-shot setting and find that performance improves with model size, with Gemma-9B bridging the gap well between traditional metrics and the Gemini-1.5-pro based metric. Finally, we fine-tune Gemma-9B on the open-source BEM answer equivalence dataset (Bulian et al., 2022), and find that we obtain a very slight improvement, and hence that it performs the best on our dev-set among the Gemma models. We call the metric obtained with this model Gemma Equivalence Metric (GEM). Note that this metric takes into account the question when comparing whether two answers are equivalent, which is unlike captioning metrics such as CIDEr which omit the question entirely. In Table 4, we report open-ended evaluations using our proposed GEM metric in addition to closed-ended MCQ accuracy. We will release GEM publicly to enable reproducible open-ended evaluations.

Table 3: **Ablations using different modalities and number of frames.** † Blind baselines with no access to the video. We show results with one open-source and one closed-source video model.

<b>Method</b>	<b>ASR</b>	<b>Num. frames</b>	<b>NEPTUNE-FULL</b>		<b>NEPTUNE-MMH</b>	
			<b>Acc. %</b>	<b>GEM</b>	<b>Acc. %</b>	<b>GEM</b>
<i>Open-source</i>						
VidoeLLaMA2 (Cheng et al., 2024a)†	No	0	38.31	4.91	30.03	0.88
VidoeLLaMA2 (Cheng et al., 2024a)	Yes	0	<b>50.15</b>	<b>37.50</b>	41.23	<b>21.83</b>
VidoeLLaMA2 (Cheng et al., 2024a)	No	1 (center)	40.88	16.56	36.27	14.16
VidoeLLaMA2 (Cheng et al., 2024a)	No	4	43.92	16.87	39.61	10.62
VidoeLLaMA2 (Cheng et al., 2024a)	No	8	44.74	16.26	41.32	15.93
VidoeLLaMA2 (Cheng et al., 2024a)	No	16	44.74	17.48	40.29	15.04
VidoeLLaMA2 (Cheng et al., 2024a)	Yes	16	49.28	32.54	<b>45.38</b>	18.18
<i>Closed-source</i>						
Gemini-1.5-pro (Reid et al., 2024)†	No	0	51.53	12.12	41.84	7.59
Gemini-1.5-pro (Reid et al., 2024)	Yes	0	76.68	<b>44.92</b>	65.76	31.20
Gemini-1.5-pro (Reid et al., 2024)	No	1 (center)	<b>55.57</b>	14.11	51.75	13.27
Gemini-1.5-pro (Reid et al., 2024)	No	150	69.31	25.76	66.70	22.85
Gemini-1.5-pro (Reid et al., 2024)	No	all	68.94	25.40	65.58	23.44
Gemini-1.5-pro (Reid et al., 2024)	Yes	all	<b>80.66</b>	<b>44.92</b>	<b>75.32</b>	<b>34.87</b>

## 5.2 BENCHMARKS

We describe all benchmarks used below. Implementation details are provided in the appendix.

**Blind Baselines:** We evaluate models using a text-only prompt in two settings: (i) we feed only the question, answer and decoys to the model (QAD baseline). (ii) we also feed ASR as an input for a QAD+ASR baseline. This helps identify questions that can be answered by prior or commonsense knowledge, or ASR only without obtaining visual information from video.

**Image Models:** We use the BLIP2-T5-XL (Li et al., 2023b) model, which contains a 1B vision encoder (Fang et al., 2023) and a 3B text-decoder (Raffel et al., 2020). We feed the center frame of the video as the visual input, with prompt “Answer in one letter” followed by the question and shuffled answer and decoys. We also evaluate some of the video models eg. Gemini-1.5-pro and VideoLLaMA2 as image models, by feeding only the center frame.

**Video Models:** We experiment with 3 different categories of VideoQA models:

- (i) Short Context MLLMs - Video-LLaVA (Lin et al., 2023), and VideoLLaMA2 (Cheng et al., 2024b). We also experiment with a simple socratic JCEF (Just Caption Every Frame) (Min et al., 2024), which consists of a VLM to extract per-frame captions and an LLM to perform reasoning on top of these captions to answer the question.
- (ii) Long Context MLLMs which are open-source, including MA-LMM (He et al., 2024a), MiniGPT4-Video (Ataallah et al., 2024), and MovieChat (Song et al., 2023).
- (iii) Long Context MLLMs which are closed-source, namely the Gemini 1.5 model family (Reid et al., 2024) and GPT-4o (Achiam et al., 2023).

**Implementation Details:** For Video-LLaVA (Lin et al., 2023) we feed 8 uniformly sampled frames (resized to a minimum side length of 320 pixels) along with the question. We reimplement JCEF from the original paper (Min et al., 2024) with updated components - i.e. 16 uniformly sampled frame captions obtained using PaLI-3 (Chen et al., 2023a), and feed them as a text prompt to Gemini-1.0-pro along with the question and decoys. For MiniGPT4-Video, we use the public codebase<sup>3</sup> which routes videos longer than 3 minutes to their Goldfish model and those shorter to their older MiniGPT-video model. We evaluate both the Gemini-1.5-pro and Gemini-1.5-flash models described in (Reid et al., 2024). We also experiment with feeding in ASR to the Gemini-1.5-pro model as well. Frame selection is as other models except that MA-LMM has 20 and 120 and MiniGPT4-Video has default 45 with the LLaMA-Video checkpoint. For MA-LMM we feed in 120 uniformly sampled frames. For GPT-4o we use the public API<sup>4</sup>. More details are provided in the appendix.

## 5.3 RESULTS

Results for all the baselines applied to the two Neptune sets (Sec. 5.1) are provided in Table 4. We provide blind baselines and modality ablations in Table 3 for VideoLLaMA2 and Gemini-1.5-pro.

<sup>3</sup><https://github.com/Vision-CAIR/MiniGPT4-video>

<sup>4</sup>accessed Sept 30th, 2024

Table 4: **Benchmarking performance on Neptune. All frames:** Visual frames extracted at 1fps. \*Computed on 10% of the results. ‡ MCQ performance is close to random.

Method	Modalities	NEPTUNE-FULL		NEPTUNE-MMH	
		Acc. %	GEM	Acc. %	GEM
Random	-	20.00		20.00	
<i>Image models</i>					
BLIP2 (Li et al., 2023b)	RGB (center frame)	34.80	9.20	28.10	8.50
<i>Short Context MLLMs</i>					
Video-LLaVA (Lin et al., 2023)	RGB (8 frames)	25.79	10.66	24.00	5.48
VideoLLaMA2 (Cheng et al., 2024a)	RGB (16 frames)	44.74	17.48	40.29	15.04
VideoLLaMA2 (Cheng et al., 2024a)	RGB (16 frames) + ASR	49.28	32.54	45.38	18.18
<i>Long Context MLLMs - open-source</i>					
MA-LMM (He et al., 2024a) (ActivityNet-QA fine-tuned)	RGB (120 frames)	20.22‡	10.67	19.51	5.04
MiniGPT4-Video (Ataallah et al., 2024)	RGB (45 frames)	24.63	5.26	22.89	6.19
MovieChat (Song et al., 2023)	RGB (150 frames)	28.96	3.79	30.30	1.01
<i>Closed-source MLLMs</i>					
VLM captions + LLM (JCEF) (Min et al., 2024)	VLM captions (16 frames)	58.51	12.27	56.45	11.50
GPT-4o (Achiam et al., 2023)	RGB (8 frames) + ASR	80.23	*49.01	72.86	
Gemini-1.5-pro (Reid et al., 2024)	RGB (all frames) + ASR	80.66	44.92	75.32	34.87
Gemini-1.5-flash (Reid et al., 2024)	RGB (all frames) + ASR	76.90	45.59	71.05	33.93

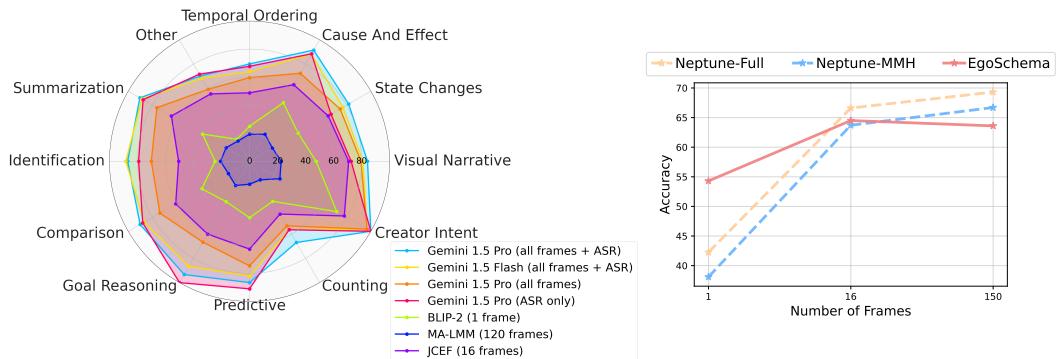


Figure 4: **Performance of different models across question types on NEPTUNE-FULL (left) and Neptune Vs EgoSchema with different frame rates (right).** On the right we show Gemini 1.5 Pro’s accuracy when linearly subsampling to 1, 16 or 150 frames. We note that (i) performance on the Neptune sets increases as more frames are provided while on EgoSchema it saturates after 16 frames and (ii) NEPTUNE-MMH is more challenging than EgoSchema.

**Single frame baselines:** We examine model performance using the BLIP2 image-only model (Tab. 4) and two video models (VideoLLaMA2 and Gemini-1.5-pro) with only the center frame of the video in Tab. 3. The larger Gemini model outperforms BLIP-2, however performance with only a single frame is much lower than with multiple frames, as expected. We also show results using Gemini-1.5-pro on the first frame of the video in Fig. 4 (right), and find that using the middle frame performs better. VideoLLaMA2 is a short context model, and we find performance saturates at 8 frames.

**Modality Ablations:** Table 3 shows that performance of Gemini-1.5-pro and VideoLLaMA2 with ASR only as input is higher than performance with multiple video frames on the NEPTUNE-FULL set, but not on the NEPTUNE-MMH set (for MCQ eval). Surprisingly, the best result of VideoLLaMA2 is obtained using ASR only and not providing image frames. In fact, if we provide 16 frames in addition to ASR (last row of the open-source block), performance drops slightly. This may be a result of attention dilution (Coleman et al., 2023), where an increasingly large context distracts the model, causing a drop in performance. For Gemini-1.5-pro on both sets however, the best performance is obtained with both frames and ASR, showcasing the complementary nature of the modalities.

**Video Models:** We see a significant gap between open-source models and Gemini-1.5-pro and GPT-4o. Interestingly, we find that open-source models that are designed specially for longer context video understanding (MA-LMM (He et al., 2024a), MiniGPT4-Video (Ataallah et al., 2024) and MovieChat (Song et al., 2023)) perform worse than VideoLLaMA2. This observation was also found by concurrent datasets such as MLVU (Zhou et al., 2024) and LVbench (Wang et al., 2024). The gap between many open-source and proprietary large MLLMs is also shown on concurrent datasets, e.g. LVbench (Wang et al., 2024), where MovieChat gets near-random results and Gemini-1.5-pro is the

state-of-the-art. One reason for this near random performance may be the domain gap between the training sets of these models (He et al., 2024a; Song et al., 2023) and Neptune – MovieChat is trained on movies and MA-LMM is designed to be fine-tuned on downstream QA datasets. By not providing a training set, we intentionally aim to assess generalization via zero-shot performance. We also note that the simple JCEF baseline, which consists of frame captions fed to an LLM for reasoning, outperforms all open-source models. The low performance of open-source models suggests Neptune may be a challenging benchmark for the future development of open-source models for long videos.

**Challenging split and Gemini Bias:** Both GPT-4o and Gemini-1.5-pro perform comparably on NEPTUNE-FULL, despite Gemini-1.5-pro being used in dataset creation, and on the NEPTUNE-MMH set, neither model is able to achieve saturated performance. This suggests that our extensive human rater step was able to help mitigate Gemini bias. This is unlike VideoVista (Li et al., 2024) which uses GPT-4 to generate QADs automatically. However the performance of GPT-4 and Gemini-1.5 on their dataset is close to saturated (98% on some categories). We note that performance falls for all models universally on the NEPTUNE-MMH set demonstrating the challenging nature of this set.

**Results on HPQ and Gemini bias:** In Tab. 2, we compare open-ended question answering performance on questions generated by our pipeline to performance on fully human written questions (HPQ) on the same set of videos. The time taken to manually create HPQ (19.03 minutes on average per question) is significantly longer than simply discarding or correcting QAs generated automatically as is done in our Neptune pipeline (10.32 minutes). While most models perform slightly worse on HPQ, overall performance is similar, suggesting that our automatic pipeline reaches the same difficulty level with roughly half the rater effort. Notably, Gemini-1.5-pro performs comparatively on both sets, suggesting that bias introduced by the model in the creation pipeline is limited.

**Video Coverage compared to EgoSchema:** In this section we investigate Gemini 1.5 Pro’s accuracy when linearly subsampling the video to 1, 16, or 150 frames. For 1 frame, we take the first frame of the video. We show results for all Neptune splits and compare them to results on EgoSchema in Fig. 4. Gemini 1.5 Pro’s performance on Neptune increases as more frames are provided, while on EgoSchema it saturates after 16 frames, suggesting Neptune is better at requiring *long* video reasoning. Note that every video in EgoSchema has 180 frames (3 mins), whereas Neptune has variable lengths, with videos up to 15 minutes long. Results with the first frame on both Neptune splits are also much lower than those on EgoSchema (54.3), pointing to higher image bias in the latter. EgoSchema also introduced the concept of a temporal certificate. We introduce a slightly modified version, which is *Model-Based*, and show that the Gemini-1.5-pro model needs more frames to answer a question correctly in Neptune, with a mean certificate of 5.39 frames (compared to 1.6 for EgoSchema). The details of this experiment are provided in the appendix.

**Open-ended results:** We find that in general, results with GEM mirror the trends demonstrated by the multiple choice eval, with the exception of the Gemini-1.5-flash and Gemini-1.5-pro results, as well as the performance of the long context open-source models. Here we find that the FLASH model actually slightly exceeds the performance of the PRO model on the FULL set, and MovieChat performs worse on the open-ended task than other baselines, while better on the MCQ evaluation. A qualitative examination of the scores with the highest disparity shows that the FLASH model seems to indeed provide better open-ended answers. Examples of this are provided in the appendix.

**Results per question type:** Performance of different models across the different question types are shown in Fig. 4. We find that “Counting”, “Temporal Ordering” and “State Change” questions are challenging for all models, pointing to areas for future work for video-language models, while “Cause and Effect” is easier. Interestingly, the Gemini-1.5-Pro model applied only to ASR without access to video frames is the best at “Goal Reasoning”, which may be because human goals in videos are often mentioned in speech. Yet as expected, it is worse at the “Visual Narrative” questions, where Gemini-1.5-Pro models with access to RGB frames do much better.

## 6 CONCLUSION

We present Neptune, a new benchmark for VideoQA with a focus on *multimodal, high-level* understanding of *long videos*. Neptune is created using a scalable pipeline for arbitrary videos that minimizes (though not omits) human verification. Benchmarks are evaluated using MCQ and open-ended evals – for which we provide a new, open-source metric. **Limitations:** The dataset may inherit biases of the Gemini model used to generate QADs. While VideoQA is a good proxy for video understanding, our dataset could be further improved by additional annotations – such as manually annotated temporal grounding, dense captions or entity labels.

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## 7 APPENDIX

### A RELATED WORKS

Here we provide an additional discussion of related works that were omitted from the main paper due to lack of space. The recently released Perception Test (Patraucean et al., 2024) consists of script-based recorded videos with manual annotations focusing on 4 broad skill areas - Memory, Abstraction, Physics, Semantics, however videos are only 23s long (avg). Like Neptune, ActivityNet-RTL (Huang et al., 2024) was constructed in a semi-automatic fashion by querying GPT-4 to generate comparative temporal localization questions from the captions in ActivityNet-Captions (Krishna et al., 2017). CinePile (Rawal et al., 2024) was generated by prompting an LLM to generate multiple-choice questions. Because it is based on movie clips, it can leverage available human-generated audio descriptions. Both ActivityNet-RTL and CinePile cover only limited domains and rely on existing annotations while Neptune covers a much broader spectrum of video types and its pipeline is applicable to arbitrary videos. Our rater stage is lightweight, unlike other works that are entirely manual (Zhou et al., 2024; Fang et al., 2024; Wang et al., 2024). In LVBench (Wang et al., 2024), even the video selection is done manually, and for MoVQA (Zhang et al., 2023b), only the decoys are generated automatically. Another recently released dataset (concurrent with our submission) is the Video-MME dataset (Fu et al., 2024). The motivation of this dataset is similar to ours, namely it covers videos of variable lengths, with 2,700 QADs covering a wide range of different question types. The main difference between Video-MME and Neptune is that the former is entirely manually annotated by the authors, while we propose a scalable pipeline which can be applied to new videos and domains automatically, and can be tweaked to include different question types with reduced manual effort. EgoSchema is the closest work to ours in motivation, but there are some key differences: (i) it is limited to egocentric videos of exactly 3 minutes each, while Neptune covers many domains and follows a more natural length distribution for online videos (16s to 15min); (ii) it relies heavily on manually obtained dense captions for egocentric videos, while our method generates captions automatically too and hence can be easily applied to any video online; and more importantly (iii) EgoSchema also has strong image and linguistic biases, while Neptune mitigates these.

Table 5: Comparison to Existing VideoQA datasets: **Ann.** Type: Annotation Type, **QAD:** Question, Answer and Decoys, **Rater V:** Rater verified manually.  $\dagger$  Movies are no longer available.  $\ddagger$  Annotations are hidden behind a test server, 500 are public. \*average/max length.

Name	Ann	Rater V	Avg. len (s)	# Vids (total/test)	# Samples (total/test)	Available
MovieQA (Tapaswi et al., 2016)	QAD	✓	200	6,771/1,288	6,462/1,258	$\times\dagger$
MSRVT-QA (Xu et al., 2017)	QA	✗	15	10,000/2,990	243,680/72,821	✓
ActivityNet-QA (Yu et al., 2019a)	QA	✓	180	5,800/1,800	58,000/18,000	✓
NExTQA (Xiao et al., 2021)	QAD	✓	44	5,440/1,000	52,044/8,564	✓
IntentQA (Li et al., 2023a)	QAD	✓	44	4,303/430	16,297/2,134	✓
EgoSchema (Mangalam et al., 2023)	QAD	✓	180	5,063/5,063	5,063/5,063	$\checkmark\ddagger$
Perception Test (Patraucean et al., 2024)	QAD	✓	23	11,600	38,000	✓
MVBench (Li et al., 2023c)	QAD	✗	16	3,641	4,000	✓
Video-Bench (Ning et al., 2023)	QAD	✓	56	5,917	17,036	✓
AutoEval-Video (Chen et al., 2023c)	QA	✓	14.6	327	327	✓
IH-VideoQA (Reid et al., 2024)	QAD	✓	6,300 (max)	125	125	$\times$
MLUV (Zhou et al., 2024)	QAD	✓	720	2K	2593	✓
<b>Neptune</b>	QAD	✓	150/901*	2,405	3,268	✓
<b>Neptune-MMH</b>	QAD	✓	159/901*	1,000	1,171	✓

## B THE NEPTUNE DATASET

### B.1 ADDITIONAL INFORMATION ON QUESTION TYPES

Neptune covers a broad range of long video reasoning abilities, which are summarised below. These question types are obtained in the Question and Answer generation stage, for which the prompt is provided in Sec. C.2.3. We provide further insights into the motivations of some of the question areas provided in the prompt below.

**Video Summarisation:** Summarise and compare long parts of the video, as well as identify the most important segments of the video.

**Visual Reasoning:** Recognize and understand visual elements in different parts of the video, as well as reason about why visual content is used (*e.g.* to convey a certain mood).

**Temporal Ordering:** Understand the timeline of events and the plot in the video.

**Counting:** Count objects, actions and events. Here we focus on higher-level counting where the same instance does not occur in all/every frame and actions are sufficiently dissimilar.

**Cause and Effect:** Understand and reason about cause and effect in the video.

**Message:** Understand the unspoken message that the audience may perceive after watching the video, which may require common sense knowledge to infer.

**State Changes:** Understand object states change over time, such as a door opening and food being eaten.

Since the questions are proposed automatically by an LLM, the question types are also generated in an open-set manner by the LLM. Hence sometimes, the LLM will generate the question type label using different phrasing - eg. ‘temporal ordering’ or ‘timeline event’. We use simple manual postprocessing to group similar question types into the same category, with a few question types that do not fall into any of the categories grouped as ‘Other’. The final *question types* released with the dataset are shown in Fig. 3 of the main paper.

### B.1.1 QUESTION TYPE DISTRIBUTION

We explain the reasons for Neptune’s current question type distribution:

- (i) We prompted the LLM that generated the questions with a set of examples of different question types and let the model choose which questions to generate.
- (ii) The model’s selection of question types depends strongly on the given video. For example, while it is always possible to ask for a video summary, it is not always possible to ask about a person’s goals, or cause and effect, because not all videos allow for these types of reasoning. This naturally leads to an imbalance of possible question types.
- (iii) Additionally, we observed that the quality of questions produced by the LLM varies strongly by question type. Therefore, after quality checking by raters, the distribution changes significantly. The strongest difference was for counting questions, as LLM-proposed questions were often too easy, *e.g.* counting the number of times a certain word is mentioned.

## B.2 DOMAINS IN NEPTUNE

A full graph of the domains in Neptune are provided in Fig. 5.

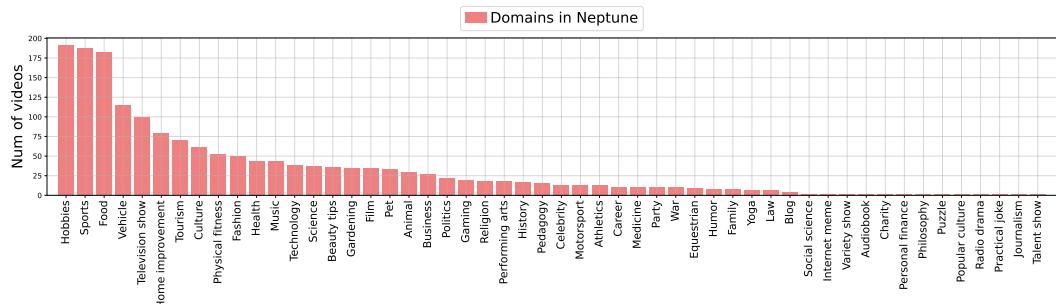


Figure 5: **Domains in Neptune:** We show the number of videos per domain category in NEPTUNE-FULL.

## C IMPLEMENTATION DETAILS

### C.1 VIDEO SELECTION

We choose the YT-Temporal-1Bn dataset (Zellers et al., 2022b) as the source for Neptune, because of its large and diverse corpus, and because of the high correlation between vision and audio transcripts.

**Safety & Content Filters:** We filter out videos with less than 100 views, that are uploaded within 90 days, and those tagged by YouTube content filters to contain racy, mature or locally controversial content. We then identify and remove static videos (eg. those that consist of a single frame with a voiceover) by clustering similar frames in a video and ensure that there is more than 1 cluster. We also identify and remove videos comprising primarily of "talking heads". To achieve this, we apply a per-frame frontal-gazing face-detector at 1fps and mark the frames where the bounding box height is greater than 20% as *talking head frames*. Then, we filter out videos where more than 30% of the frames are talking head frames. These thresholds are chosen based on an F1-score on a small dev set of 50 manually annotated videos.

**Diversity Sampling:** From the filtered set of videos, we sub-sample 100,000 videos to boost both semantic and demographic diversity. First, we cluster the videos based on video-level semantic embeddings and tag each video with a cluster id. Second, we tag each video with the perceived age and gender demographic information contained in the video. Third, we obtain a joint distribution of semantics (cluster id) and demographics (perceived age and gender) and apply a diversity boost function (Kim et al., 2022) on the joint distribution. Finally, we sample from videos from this distribution. Fig. 6, shows the down-sampling of over-represented cluster ids before and after applying the filter. We then uniformly sub-sample the videos further to reach the desired dataset size.

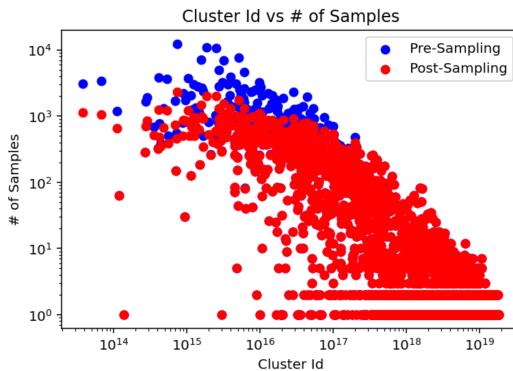


Figure 6: **Diversity sampling:** We show the change in cluster distribution after diversity sampling.

## C.2 PROMPTS FOR DATA GENERATION

In this section we provide some of the prompts used for generating Neptune.

### C.2.1 PROMPT FOR FRAME CAPTIONING

We use the following prompt to obtain a caption for each video frame:

Answer the following questions about the given image. Then use the information from the answers only, and write a single sentence as caption. Make sure you do not hallucinate information.

Question(Mood): Describe the general mood in the image as succinctly as possible. Avoid specifying detailed objects, colors or text.

Question(Background): Describe the background of the image as succinctly as possible. Avoid specifying detailed objects, colors or text. Eg: The background is a parking lot, playground, kitchen etc.

Question(Person): Is there any person in the image. If yes, describe them and what are they doing here? If no, say no person.

Question(General): Describe the image as succinctly as possible. Avoid specifying detailed objects, colors or text.

Question(Text): Is there any text? What does it say?

Result template:

**Answer(Mood):** A succinct description of what is happening in the image with the general mood.

**Answer(Background):** A succinct description of the background scene in the image and what is happening.

**Answer(Person):** If there are people in the image, a succinct description.

**Answer(General):** A succinct description of the image.

**Answer(Text):** Reply if there is any text, where it is placed and how it is related to what is happening in the image.

**Caption:** A couple of sentences summarizing the information given by the answers about mood, background, person, general and text.

With the above format as template, generate the response for the new image next.

### C.2.2 PROMPTS FOR AUTOMATIC VIDEO CAPTIONING

A visual overview of the video captioning stage is provided in Fig. 7. We describe the prompts for each stage below:

#### **Shot level captions:**

Using the shot boundaries the 1fps frame captions are summarized into shot level descriptions with the following prompt:

Summarize these sentences in dense short sentences: [list of frame captions in the shot]

#### **Topic and Description Pairs:**

If ASR exists, topic and description pairs are obtained from ASR using the following prompt:

**\*\*Task:\*\*** Take a deep breath and give me the structural topics of the Youtube video below using the transcript. Give up to 5 Topic and Description pairs using output format. **\*\*Transcript:\*\*** transcript

#### **Shot Clustering:**

Take a deep breath and identify the sequential topic structure of this video using the "{head\_topic}" in Scenes. A part of the video script is provided as a set of Scenes and in each scene, visual captions and transcript sentences are provided. The overall suggested structure from the transcript is provided as well. Assign every scene in this part of the script to one topic structure. For each scene, the visual captions should support and relate the topic. If the support or relation is not strong create a new topic and assign the scene to it. Reevaluate the suggested structure from the transcript and make sure all scenes are assigned to the best associated topics. Keep output length to be less than {max\_output\_characters} characters.

**\*\*Output Format:\*\*** XML output where topic has the following children (description, topic\_scenes, story) <topic> <description>The description of the topic</description> <topic\_scenes>Comma separated scene number(s) related to this topic<topic\_scenes> <story>Summarized caption that describes what happens and what's shown for this topic in the scenes by combining visual caption and transcript sentences of the related scenes</story> </topic>

**\*\*Suggested Structure:\*\*** {initial\_structure\_from\_ASР\_if\_exists}

**\*\*Context:\*\*** {summary\_of\_title\_and\_description}

**\*\*Video Script:\*\*** {video\_script}

#### **Segment Captions:**

Consecutive shots of the same topic are then merged as one segment. Shots of the same topic that are not contiguous are treated as separate segments (see Fig. 7). We then generate dense captions for

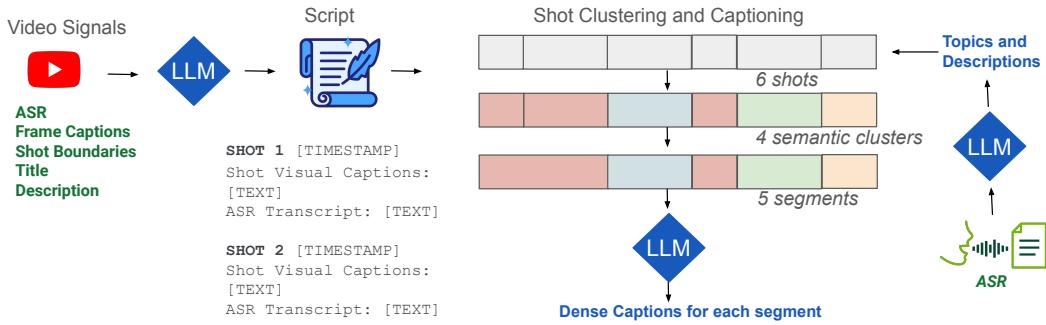


Figure 7: **Video Captioning:** We extract dense segment level captions automatically for each video. This is done by prompting an LLM using video signals (ASR, frame captions, shot boundaries and metadata) with various different steps and prompts.

each segment using the prompt below:

```
**Task:** You are the expert in video description writing. Use the information "Partial Script" to improve the "Initial Description" by adding the missing information either from visual or transcript. The video context is also given to help you interpret the script. Only add information that is in the "Partial Script". Make the output concise and compact with less or the same length as Initial Description. The updated video description is plain text. Your answer should follow the output format. Keep output length to be less than max_output_characters characters.
```

```
**Initial Description:** shared_topic_cluster_caption
```

```
**Output Format:** XML format like below <updated_description>updated video description text</updated_description>
```

```
**Partial Script:** doc_segment
```

#### Visual Support Caption

To extract better visual description of the segment that will be used for QA generation in the next phase, an extra step is performed to get visual support for each segment. That visual support is stored separately in conjunction with the dense caption for the segment. For this purpose, the dense caption from the previous step is used alongside the shot level visual captions. The following LLM prompt is used to extract the visual support:

```
**Task:** I provide video scene information and your job is to summarize the exact elements from "Visual Captions" that directly support the "Scene Story" of the scene below. The visuals of the scene is broken down to shots and each shot is described in a line of text in the Visual Captions.
```

```
**Scene Story:** dense_caption_for_the_segment
```

```
**Visual Captions:** visual_captions_of_the_segment
```

```
**Output Format:** Plain text with at most 200 words summarizing the supporting visual elements.
```

#### C.2.3 GENERATING QUESTIONS AND ANSWERS

I want you to act as a rigorous teacher in the "Long-term Video Understanding" class. Let's test your students' in-depth comprehension!

Understanding: I'll provide you with the following:

- Dense Captions: A detailed breakdown of the video, including key moments and timestamps. Analyze this carefully.

Your Task: Craft {target\_number} Challenging Short-Answer Questions

Requirement:

- Challenge: Demonstrate your ability to create challenging, insightful short-answer questions about the video. These shouldn't test simple recall only. Aim to probe understanding of relationships, motives, subtle details, and the implications of events within the video.
- Diversity: Design a variety of question types (more on this below).
- Specificity: Each question must be self-contained and laser-focused on a single concept or event from the video. Avoid compound or overly broad questions.
- Answers: Model the ideal answer format: Brief, accurate, and rooted directly in evidence from the video's content.
- Video-Centric: Stay true to what's explicitly shown or stated in the video. Avoid relying on outside knowledge or speculation. Design questions so the correct answer cannot be easily determined without carefully analyzing the video.
- Minimize Information Leakage: For question types like ranking or ordering, ensure that the order of candidates or options listed in the question doesn't inadvertently reveal the correct answer. Shuffle them to maintain neutrality.
- Content-First: Timestamps and section titles within the captions are there for guidance. Do not explicitly refer to those markers in your questions or answers. Focus on the events and elements themselves.
- Unambiguous: Ensure each question has a single, clearly defined correct answer. Avoid questions that are open to multiple interpretations (e.g., counting elements where viewers might disagree).
- Visual Elements: Questions focused on visual reasoning or visual narratives should emphasize the interpretation of the visuals. Keep the question minimal, letting the answer describe the specific visual elements in detail.

You want to test students' capabilities of understanding the video, including but not limited to the following aspects:

- Ability: Summarize and compare long parts of the video.
- Ability: Compress information from the video rather than just listing the actions that happened in the video.
- Ability: Identify the most important segments of the video.
- Ability: Recognize and understand the visual elements in different parts of the video.
- Ability: Understand the timeline of events and the plot in the video.
- Ability: Count objects, actions and events. Focus on higher-level counting where the same instance does not occur in all/every frame and actions are sufficiently dissimilar.
- Ability: Understand and reason about cause and effect in the video.
- Ability: Understand the unspoken message that the audience may perceive after watching the video, which may require common sense knowledge to infer.
- Ability: Understand the visual reasoning of why and how important visual content is shown in the video.
- Ability: Understand the visual narrative of the video and the mood of the video and which visual elements do contribute to that.
- Ability: Understand object states change over time, such as door opening and food being eaten.

Presentation

- QUESTION: Introduce each question as "QUESTION 1, 2, 3: (capability) full question". - ANSWER: Follow the format "CORRECT ANSWER: correct answer".

Good example questions: - Question (counting): How many ingredients are added to the bowl in total throughout the video? Correct Answer: 3.

- Question (goal reasoning): What is the purpose of the man standing in front of the whiteboard with a diagram on it? Correct Answer: To explain the features and capabilities of the vehicle.

- Question (cause and effect): How does the document help people to be happier? Correct Answer: It helps people to identify and focus on the things that make them happy, and to develop healthy habits.

- Question (timeline event): In what order are the following topics discussed in the video: history of pantomime, importance of pantomime, mime as a tool for communication, benefits of pantomime? Correct Answer: Mime as a tool for communication, history of pantomime, importance of pantomime, benefits of pantomime.

- Question (predictive): What happens after the man jumps up and down on the diving board? Correct Answer: He jumps into the pool.

- Question (summarization): What is the overall opinion of the reviewers about Hawaiian Shaka Burger? Correct Answer: The food is good, but the patties are frozen.

- Question (creator intent): What message does the video creators try to send to the viewers? Correct Answer: Nature is essential for human well-being.

- Question (visual-temporal): What color is the scarf that Jessica wears before she enters the restaurant? Correct Answer: Red.

- Question (visual narrative): How does John's overall facial expression contribute to the explanation of the financial situation that is described in the video? Correct Answer: He shows sad feelings and expression when he described the financial collapse of the company which adds to the sense of empathy that video describes.

- Question (visual reasoning): What was shown to support the effects of a high cholesterol diet in the video? Correct Answer: Video demonstrates how cholesterol gradually clogs blood vessels, using an animation to illustrate the cross-section of vessels and the buildup of plaque.

Bad example questions because it can be answered by common sense. -

Question (counting): How many players are there in a soccer team? Correct Answer: 11.

Bad example questions because it asks for trivial details. - Question

(counting): How many times the word 'hurricane' is said in the video? Correct Answer: 7.

Bad example questions because the summary of topics are subjective and ambiguous. - Question (timeline event): List the sequence of topics Grace discusses in the video, starting with the earliest. Correct Answer: Getting ready for a photoshoot, attending a baseball game, showing off her new outfit, playing a Wayne's World board game, and discussing her upcoming week.

Dense Caption with Timestamps: {video\_inputs\_str}

#### C.2.4 GENERATING DECOYS FROM QUESTIONS AND ANSWERS

Role: You are a rigorous teacher in a "Long-term Video Understanding" class. You will assist students in developing strong critical thinking skills. This requires creating sophisticated test questions to accompany video content.

Understanding: I will provide:

- Dense Captions: A breakdown of the video, including structure, key events, and timestamps.
- Target Questions & Answers: A set of  $\{\text{target\_number}\}$  questions about the video, along with their correct answers.

Task: Generate High-Quality Multiple-Choice Questions

1. Analyze: Carefully study the dense captions, questions, and correct answers. Familiarize yourself with the nuanced details of the video content.
2. Decoy Design: For each target question, generate  $\{\text{decoy\_number}\}$  incorrect answers (distractors). These distractors must be:
  - Challenging: Plausible to the point where students need deep content understanding and critical thinking to choose the correct answer.
  - Stylistic Match: Mimic the style, tone, and complexity of the correct answer.
  - Similar Length: Keep length close to that of the correct answer, preventing students from eliminating choices based on length differences.
  - Factually Relevant: Related to the video content, even if slightly incorrect due to a detail change, misinterpretation, or logical fallacy.
  - Reasonable: Each decoy should be something that could be true, making simple elimination impossible.

Specific Techniques for Distractor Creation

- Subtle Tweaks: Alter a minor detail from the correct answer (e.g., change a time, location, or name).
- Confusing Similarity: Use a concept from elsewhere in the video that seems related but applies to a different context.
- Misdirection: Introduce a true statement related to the video's theme but not directly answering the question.
- Order Shuffling: If the question involves the order of events, subtly rearrange the order within the distractors.

Presentation:

- QUESTION: Repeat the provided question faithfully (e.g., "QUESTION 1 (Capability): ...")
- CORRECT ANSWER: Repeat the correct answer (e.g., "CORRECT ANSWER: ...")
- WRONG ANSWERS: List each wrong answer on a separate line without using letters to label choices (e.g., "WRONG ANSWER 1: ...", "WRONG ANSWER 2: ...")

\*GOOD\* Example: Question: What are the three main challenges that the college is taking on? Correct Answer: Food scarcity, pollution, and disease. Wrong Answer 1: Global warming, deforestation, and poverty. Wrong Answer 2: Hunger, homelessness, and crime. Wrong Answer 3: Obesity, malnutrition, and food insecurity. Wrong Answer 4: Food waste, water shortages, and air pollution.

\*BAD\* examples where the decoys format is different from correct answer:  
Question: What color is the shirt that the woman is wearing? Correct Answer: Black. Wrong Answer 1: The woman is wearing a white shirt. Wrong Answer 2: The woman is wearing a blue shirt. Wrong Answer 3: The woman is wearing a green shirt. Wrong Answer 4: The woman is wearing a red shirt.

\*BAD\* examples because only the correct answer is in positive sentiment.  
Question: What is the overall sentiment of the man in the video? Correct Answer: He is overjoyed with his new gift. Wrong Answer 1: He is upset his gift is not big enough. Wrong Answer 2: He is sad about life in

general. Wrong Answer 3: He is upset the gift is not great. Wrong Answer 4: He seems down and unhappy.

Dense Caption with Timestamps: {video\_inputs\_str}

Question and Correct Answer: {question\_and\_answer\_str}

### C.2.5 QAD FILTERING

The following prompt is used to filter out questions that can solve from QADs alone.

**Instructions:**

Carefully analyze the following question and options. Rank the options provided below, from the most likely correct answer to the least likely correct answer. Please respond with "ANSWER" and "EXPLANATION".

Your response should be in the following format:

\* ANSWER: [Letter of the ranking, split by greater than symbol. (e.g., "ANSWER: A > B > C > D > E")].

\* EXPLANATION: [Provide a brief explanation of your choice. Do not repeat the option.]

QUESTION: {question\_str}

Options: {options\_str}

Please provide your response below.

### C.3 HUMAN RATING AND CORRECTION OF QADs

We provide a screenshot of the UI used by raters to annotate automatically generated QADs in Fig. 8. Note that if any of the four options under the ‘Is the question valuable’ field are not selected, then the question is discarded from the dataset. We made sure to train raters using training raters (with detailed decks and feedback rounds), as well as applying rater replication (we used 3 raters per question independently), and rater pipelining (having an experienced rater verify the answer from a previous rater) in order to correct hallucinations and other mistakes, and discard QADs that were inappropriate. Overall, of the total 11,030 QADs that we obtained automatically, 7,762 (70%) were discarded by raters.

### C.4 FILTERING SUBSETS

Here we provide details for how we select the thresholds used to create the NEPTUNE-MMH and NEPTUNE-MMA subsets. For both subsets, we filtered NEPTUNE-FULL with the QAD filter described in Sec. 4.4. For NEPTUNE-MMA, we additionally filtered out QADs that human raters marked as requiring only the audio modality and answer (see Sec. 4.5). We refer to this as the “rater test”. For NEPTUNE-MMH, we instead applied the ASR filter (Sec. 4.4). Both QAD and ASR filters were run by prompting an LLM (Gemini 1.0 Pro) three times, each time with a different random seed and then removing QADs that the LLM answered correctly at least X out of three times, where X is the threshold for the test.

Fig. 9 shows how choosing different thresholds affects dataset size and accuracy scores. The top row shows the choices for the NEPTUNE-MMH subset. Raters marked almost half of the questions as answerable from audio only, so the rater filter already cuts the dataset size in half. Successively applying the QAD filter with increasing thresholds reduces data size up until less than 25%. We benchmark three models on the different subsets that have access to ASR only, vision only, or both vision and ASR, respectively. As expected, all three models show declining performance, with the ASR-only model showing the biggest losses. This suggests that all models were inferring the correct answer from the QAD only, which the filter successfully mitigates. The vision-only model gains slightly from removing QADs that fail the rater test, which is expected as the test removes QADs that rely on audio, which the model does not have access to. However, like for the other models, its accuracy declines when adding the QAD test.

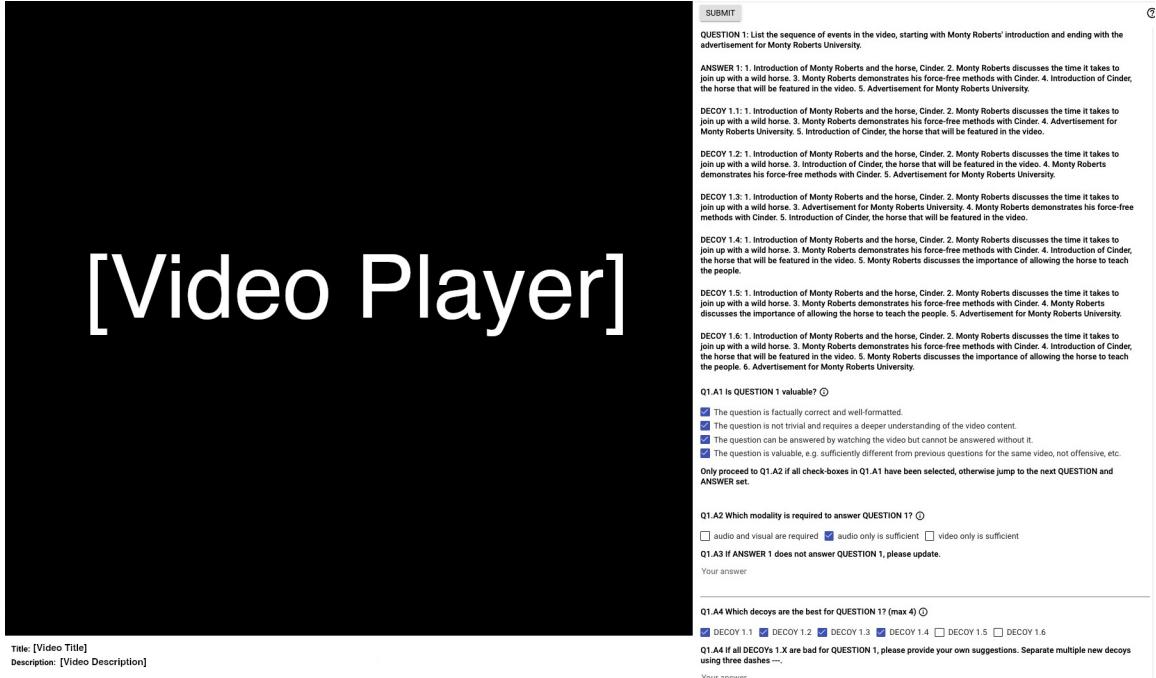


Figure 8: Screenshot of rater UI.

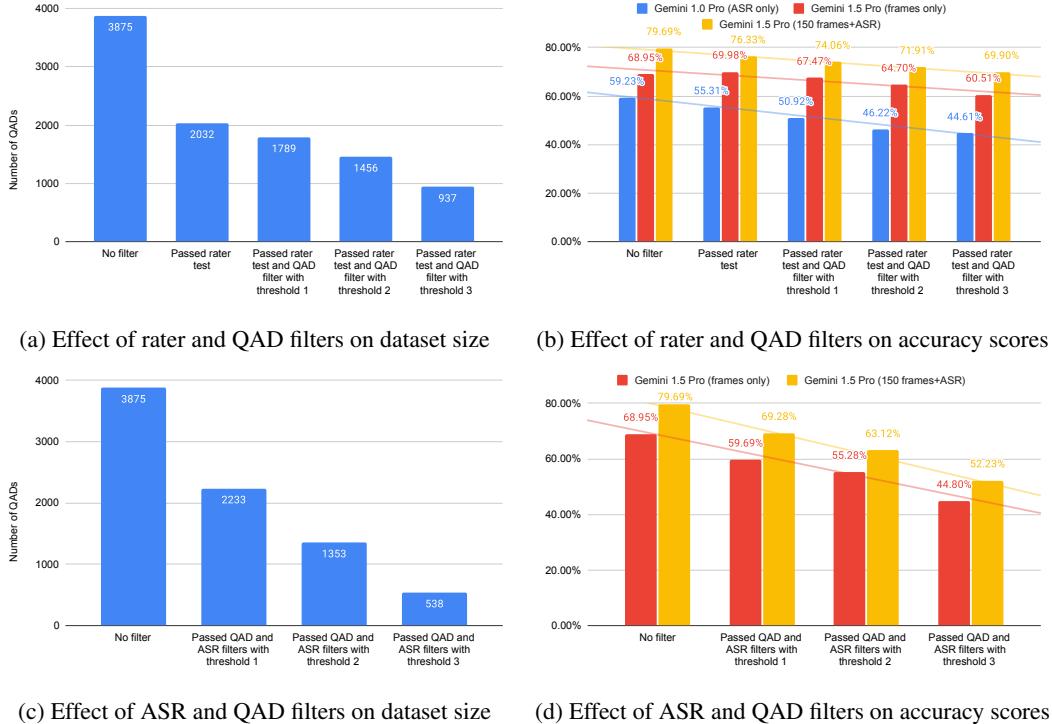


Figure 9: Effect of filtering thresholds for the NEPTUNE-MMH (top row) and NEPTUNE-MMA (bottom row) subsets.

The bottom row of Fig. 9 shows the choices for the NEPTUNE-MMA subset where we use the ASR filter and the QAD filter with identical thresholds. This filter set has a stronger effect on the dataset size, reducing it to less than 15% of its original size at the highest threshold. Because the ASR-only

model was used for the ASR filter, we exclude it from the accuracy comparison. The vision-only and vision+ASR models both show declining accuracy with increasing thresholds. As expected, the accuracy of the vision+ASR model declines faster. The effect of this filter set on the accuracy is much stronger than that of the above filter set, suggesting that it increases the difficulty of the dataset more strongly. Even the vision-only model declines faster than above, suggesting that this filter set generally removes easier questions, even those that rely on vision only.

For both filtered sets, we opted to set the threshold to two, which in both cases significantly increases the dataset difficulty while still preserving enough QADs for statistically meaningful evaluation metrics. We noticed that when setting the threshold to three, there were less than five QADs left for some question types, preventing robust accuracy estimation for these tasks.

## C.5 IMPLEMENTATION DETAILS FOR BENCHMARKS

### C.5.1 BLIND BASELINES

For the Gemini-1.5-pro baseline with text only the prompt used was: “Carefully analyze the question and all available options then pick the most probable answer for this question”

### C.5.2 VIDEO-LLAVA

For Video-LLava the following prompt was used - "Pick a correct option to answer the question. Question: question Options: options ASSISTANT:".

### C.5.3 VIDEOLLAMA2

During inference, we uniformly sampled 8 frames from each video. Each frame undergoes padding and resizing to a standardized dimension. The pre-processed frames are then fed into the image encoder. These steps are set as default in the inference script provided by videoLlama2.

**QAD Prompt:** \_PROMPT\_TEMPLATE = """Pick a correct option number to answer the question. Question: {question} Options: {options}"""

**OE Prompt:** Question: {question}

Output post processing: We eliminated extra characters and spaces using regex to get the final ID of the predicted option.

### C.5.4 MINIGPT4-VIDEO

We set the 300 maximum number of output tokens to be 300 for the open-ended task and 10 for the multiple choice eval. The prompts are as follows:

\_PROMPT\_TEMPLATE\_MCQ = """Question: select the correct option for this task: question Options: options. Output format: [OPTION]: [Reason]"""

\_PROMPT\_TEMPLATE\_OPEN\_ENDED = """Question: question Answer:"""

### C.5.5 MA-LMM

We set the 300 maximum number of output tokens to be 300 for the open-ended task and 300 for the multiple choice eval. The prompts are as follows:

\_PROMPT\_TEMPLATE\_MCQ = """Question: select the best choice for this task: question Options: options Answer:"""

\_PROMPT\_TEMPLATE\_OPEN\_ENDED = """Question: question Answer:"""

## C.5.6 GPT-4O PROMPTS

### Open-ended evaluation with transcript

You are an expert in video understanding and question answering. You can analyze a video given its image sequence and transcript and answer questions based on them.

{video\_frames}

Video Transcript: {transcript}

Answer the question using the image sequence. Do not describe the frames just answer the question. Question: {question}

### **Open-ended evaluation without transcript**

You are an expert in video understanding and question answering. You can analyze a video given its image sequence and answer questions based on them.

{video\_frames}

Answer the question using the image sequence. Do not describe the frames just answer the question. Question: {question}

### **Multiple-choice evaluation with transcript**

You are an expert in video understanding and question answering. You can analyze a video given its image sequence and transcript and answer questions based on them.

{video\_frames}

Video Transcript: {transcript}

Answer the question using the image sequence. Do not describe the frames just answer the question by identifying the choice. Question: {question} Choices: {choices} Please identify the correct CHOICE and explain your reasoning concisely. Output Format: [CHOICE]: [REASON]

### **Multiple-choice evaluation without transcript**

You are an expert in video understanding and question answering. You can analyze a video as an image sequence and answer questions based on that.

{video\_frames}

Answer the question using the image sequence. Do not describe the frames just answer the question by identifying the choice. Question: {question} Choices: {choices} Please identify the correct CHOICE and explain your reasoning concisely. Output Format: [CHOICE]: [REASON]

## C.6 COMPUTE RESOURCES

The compute heavy part of the project was image frame captioning (as this involves reading high dimensional pixel data). The rest of the pipeline involves largely text-only LLMs and hence was less compute heavy. We estimate that the entire project in total took roughly 256 TPU v5e running over a period of 50 days.

## D ADDITIONAL DETAILS FOR GEM

### D.1 CREATION OF GEM EQUIVALENCE DEV SET

To create a development set that allows us to estimate the accuracy of different open-ended question answering metrics on Neptune, we sampled 97 question-answer pairs from the dataset and generated 3 candidate answers per question by prompting VideoLLAVA (Lin et al., 2023), Gemini-1.5-pro (Reid et al., 2024) and MA-LMM (He et al., 2024b) to write a free-form answer for each question without looking into the decoys or ground truth. We then manually annotated these responses between 0 and

1 by comparing it to the ground truth answer. We made sure that the annotators are blind to the model to avoid any bias. The resulting set has 292 equivalence pairs with an average score of 0.32, with 85 examples having score greater 0.5 and 206 examples with score less than 0.5

## D.2 BENCHMARKING ON THE DEV SET

In Table. 1, we evaluate several open-ended metrics on our dev set. The task of the metric is to classify whether the open-ended response and ground-truth answer are equivalent or not. We report F1-scores to balance false-positives and false-negatives. We evaluate both traditional rule-based metrics such as CIDEr and ROUGE-L, as well as established model-based metrics such as BEM(Bulian et al., 2022). We also try using Gemini-1.5-pro (Reid et al., 2024) as an LLM based equivalence metric (by prompting it to estimate equivalence). First, we note that as expected, Gemini-1.5-pro correlates well with the human ground-truth annotation of the set, achieving a high F1-score of 72.5. However, given that Gemini is not open-source and proprietary, any change in the model can affect all the prior results in an external leader-board making it challenging as a metric. Traditional rule-based metrics perform much worse than Gemini-1.5-pro on this dev set as they are n-gram based and struggle to handle the diversity of domains and styles in the open-ended responses. The BERT model based BEM metric (Bulian et al., 2022) performs similarly, achieving an F1-score of 61.5.

Next, we evaluate lightweight open-source language models Gemma-2B (Team et al., 2024a), Gemma-7B (Team et al., 2024a) and Gemma-9B (Team et al., 2024b) in a zero-shot setting and find that performance improves with model size, with Gemma-9B bridging the gap well between traditional metrics and the Gemini-1.5-pro based metric. Finally, we fine-tune Gemma-9B on the open-source BEM answer equivalence dataset (Bulian et al., 2022), and find that Gemma-9B finetuned on the BEM dataset performs the best on our dev-set. We name this metric *GEM*.

## D.3 IMPLEMENTATION DETAILS

We use instruction-tuned variants of the Gemma models (gemma-it-2b, gemma-it-7b and gemma-it-9b) for our experiments. To develop a prompt, we experiment with several variations in a zero-shot setting and measure the performance on the dev-set. Our final prompt is shown below. To ensure responses occur in a standard format, we simply measure the softmax-probability over "TRUE" response indicating the statements are equivalent and "FALSE" response indicating the statements are not equivalent. For each model, the threshold over probability is chosen to maximize the F-1 score on dev set. To finetune Gemma models on BEM dataset, we tokenize the same prompt as used in the zero-shot setting and train it using prefix-LM tuning for 10000 iterations using a learning rate of  $1e - 6$ . For evaluation, we truncate the open-ended responses to 100 words, use a decode cache size of 1024 and threshold the softmax probability of the LM using the chosen threshold from dev-set.

```
<start_of_turn>user
Answer Equivalence Instructions:
```

```
Carefully consider the following question and answers.
You will be shown a "gold-standard" answer from a human annotator,
referred to as the "Reference Answer" and a "Candidate Answer".
Your task is to determine whether the two answers are semantically
equivalent.
```

In general, a candidate answer is a good answer in place of the "gold" reference if both the following are satisfied:

1. The candidate contains at least the same (or more) relevant information as the reference, taking into account the question; in particular it does not omit any relevant information present in the reference.
2. The candidate contains neither misleading or excessive superfluous information not present in the reference, taking into account the question.

Your response should be one word, "TRUE" or "FALSE", in the following format:

ANSWERS\_ARE\_EQUIVALENT: [TRUE or FALSE]

Question:

"{}"

Candidate Answer:

"{}"

Reference Answer:

"{}"

Please provide your response below.

<end\_of\_turn>

<start\_of\_turn>model

ANSWERS\_ARE\_EQUIVALENT:

#### D.4 QUALITATIVE EXAMPLES FOR METRIC

Below, we provide some qualitative examples of our metric applied to the predictions provided by the baseline models Video LLaMA2([Cheng et al., 2024a](#)), Gemini-1.5-flash ([Reid et al., 2024](#)) and Gemini.1.5-pro ([Reid et al., 2024](#)). We find that Gemini-1.5-flash responses are qualitatively slightly better than Gemini-1.5-pro responses as they contain less hallucinations. Furthermore, we find that with a single frame as input, Gemini-1.5-pro usually responds with a variation of "This information is not present in the provided frame" instead of making an educated guess. This is unlike the case of multiple choice questions where the model commits to one of the choices. These aspects are reflected in the results presented in Table.4 and Table.3. We also find that the metric fails often in the questions about listing items / events in order. In such cases, the model is biased towards accepting the response (false positives) even if the order is incorrect provided the items / events are present in the candidate response.

Question: Compare the Pampered Chef Veggie Strip Maker to a food processor in terms of their effectiveness in making cauliflower rice.

Answer: The Veggie Strip Maker is more effective than a food processor in making cauliflower rice because it prevents the cauliflower from becoming mushy.

Video LLaMA2: Both the Pampered Chef Veggie Strip Maker and a food processor can be effective in making cauliflower rice, but they differ in their methods of operation and the resulting texture of the rice. The Pampered Chef Veggie Strip Maker is a kitchen appliance designed specifically for making vegetable strips, including cauliflower rice. It uses a grating mechanism to create rice-like pieces by shredding the cauliflower. This method can produce a relatively uniform and rice-like texture. On the other hand, a food processor is a versatile kitchen appliance that can also be used to make ...

GEM Equivalence: False

Gemini-1.5-flash: The Pampered Chef Veggie Strip Maker makes cauliflower rice that is less mushy than a food processor.

GEM Equivalence: True

Gemini-1.5-pro: The Pampered Chef Veggie Strip Maker is more effective than a food processor because it doesn't make the cauliflower mushy.

GEM Equivalence: True

Question: How does the use of behavioral training help in the process of taking foot x-rays on elephants?

Answer: Behavioral training encourages elephants to willingly

participate in their healthcare, making the process of taking foot x-rays less stressful for both the elephants and the caretakers.

Video LLaMA2: The use of behavioral training plays a crucial role in the process of taking foot x-rays on elephants. By training the elephants to follow commands and stand on a platform, it allows the caretakers to safely and effectively capture the x-rays of the elephants' feet. This training helps to ensure that the elephants remain still and cooperative during the x-ray process, minimizing any potential harm or discomfort. Additionally, the behavioral training helps to build a positive relationship between the elephants and their caretakers, fostering trust and cooperation. Overall, the use of behavioral training enhances the accuracy and efficiency of the

GEM Equivalence: True

Gemini-1.5-flash: Behavioral training allows the elephants to willingly participate in the training sessions and participate in their own health care.

GEM Equivalence: True

Gemini-1.5-pro: Behavioral training allows the elephants to willingly participate in the x-ray process by presenting their feet for imaging.

GEM Equivalence: True

Question: What are the key features of the Adam Purvis Progeny knife's blade?

Answer: The Adam Purvis Progeny knife's blade is made of 3.4-inch M390 steel. The blade shape is useful, simple, and highly effective, the edge is very sharp, featuring a stonewash finish on the primary bevels and a horizontal satin on the flats. It is exceptionally sharp and has a 150 thousandths stock thickness, making it suitable for everyday carry tasks.

Video LLaMA2: The Adam Purvis Progeny knife's blade is made of S35VN steel, which is known for its high strength and excellent edge retention. The blade has a flat ground and a hollow grind, which allows for a thin and sharp edge. Additionally, the blade has a black and silver color scheme, giving it a sleek and modern appearance.

GEM Equivalence: False

Gemini-1.5-flash: The Adam Purvis Progeny knife's blade is made of M390 steel, has a modified sheepsfoot style, and is ground very thinly for a sharp edge.

GEM Equivalence: False

Gemini-1.5-pro: The Adam Purvis Progeny knife features a 3.4-inch M390 steel blade with a modified sheepsfoot shape, thin grind, sharp edge, and a stonewashed finish on the bevels with a satin finish on the flats.

GEM Equivalence: True

Question: How does interacting with civilians in nearby villages enhance cadets' leadership skills?

Answer: Engaging with civilians in nearby villages allows cadets to develop respectful communication and relationship-building skills, which are essential for effective leadership in various situations.

Video LLaMA2: Interacting with civilians in nearby villages enhances cadets' leadership skills by providing them with real-world experiences and opportunities to apply their knowledge and training in a practical setting. By engaging with the local community, cadets learn to communicate effectively, build trust, and foster positive

relationships with people from diverse backgrounds. This hands-on experience helps them develop their interpersonal skills, cultural awareness, and problem-solving abilities, all of which are crucial for successful leadership in various situations. Additionally, interacting with civilians allows cadets to gain a deeper understanding of the challenges and needs of the community, which can inform their decision-making and ...

GEM Equivalence: True

Gemini-1.5-flash: Interacting with civilians in nearby villages teaches cadets how to speak to people respectfully and build trust.

GEM Equivalence: True

Gemini-1.5-pro: It teaches them how to speak to people.

GEM Equivalence: False

Question: List the sequence of topics discussed in the video, starting with the earliest.

Answer: 1. Introduction of the GAN356 AIR cube and its unique features. 2. Discussion of the GAN356 AIR's weight and GES (Gan Elasticity System) springs. 3. Lubrication, tensioning, and personal experience with the GAN356 AIR's performance. 4. Assessment of the GAN356 AIR's performance, including its smoothness, speed, corner-cutting, and tendency to lock up. 5. Overall evaluation of the GAN356 AIR, including its strengths and weaknesses, and recommendations for potential buyers.

Video LLaMA2: 1. Introduction to the video and the Rubik's Cube. 2. Explanation of the different types of Genuine Handcubes. 3. Demonstration of how to solve the Rubik's Cube, including the various algorithms and techniques used. 4. Showcasing of the different colors and types of Rubik's Cubes available. 5. Conclusion and closing credits.

GEM Equivalence: False

Gemini-1.5-flash: The video starts with an introduction of the GAN 356 Air cube, then discusses its features, including the GES system and its light weight. The reviewer then shares their opinion on the different GES springs and their effect on the cube's feel. The video continues with a discussion on the cube's performance, including its smoothness, speed, and tendency to lock up. Finally, the reviewer concludes with a recommendation for viewers who might be interested in purchasing the cube.

GEM Equivalence: True

Gemini-1.5-pro: The video discusses the main features of the Gan 356 Air, the different types of springs, the weight and price of the cube, the reviewer's experience with the cube, and the reviewer's overall opinion of the cube.

GEM Equivalence: False

Question: In what order are the following events mentioned in the video: introduction of the wallet, features of the wallet, and care instructions?

Answer: Introduction of the wallet, features of the wallet, care instructions.

Video LLaMA2: The video begins with the introduction of the wallet, followed by a description of its features, and concludes with instructions on how to care for the wallet.

GEM Equivalence: True

Gemini-1.5-flash: The speaker introduces the wallet, then describes

its features, and finally mentions the care instructions.  
 GEM Equivalence: True  
 Gemini-1.5-pro: Introduction of the wallet, care instructions,  
 features of the wallet.  
 GEM Equivalence: False

## E MODEL-BASED TEMPORAL CERTIFICATE

The idea of a temporal certificate was introduced by EgoSchema (Mangalam et al., 2023) as a way of capturing the intrinsic temporal understanding length for *long video* QA datasets. It is defined as ‘the length of the video a human verifier needs to observe to be convinced of the veracity of the marked annotation’. While the authors used it to uncover flaws in existing long video QA datasets, as well as to provide a difficulty measure independent of video length, we find that it has the following drawbacks: (i) it does not take into account the *length of time* or the *effort* taken by the annotator themselves, to find the correct time span in videos; (ii) it requires manual annotation from expert annotators to measure; and finally (iii) is subjective.

As an attempt to mitigate these issues, we introduce a slightly modified version of the temporal certificate, which is *Model-Based*. We calculate this certificate using 129 samples from Neptune and EgoSchema, respectively. For this experiment we used Gemini 1.5 Pro, with one “driver” model run to answer the question and two other model runs with different random seeds to verify if the answer was not correct by random chance. Along with the question and options, we provided video clips of various lengths from the center of the video, and at various fps, as shown in Fig. 10.

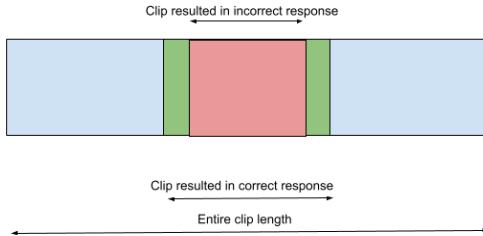
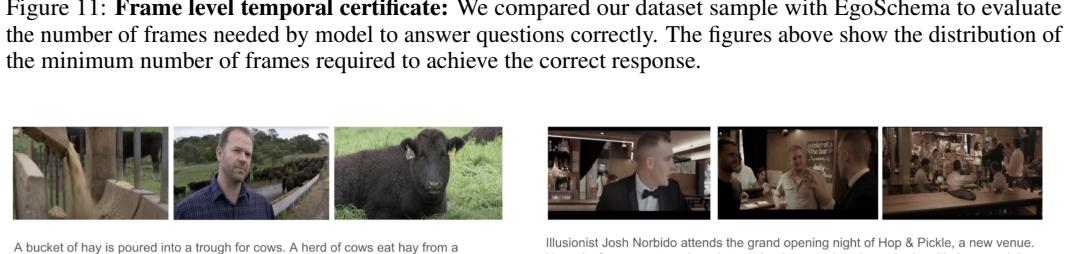
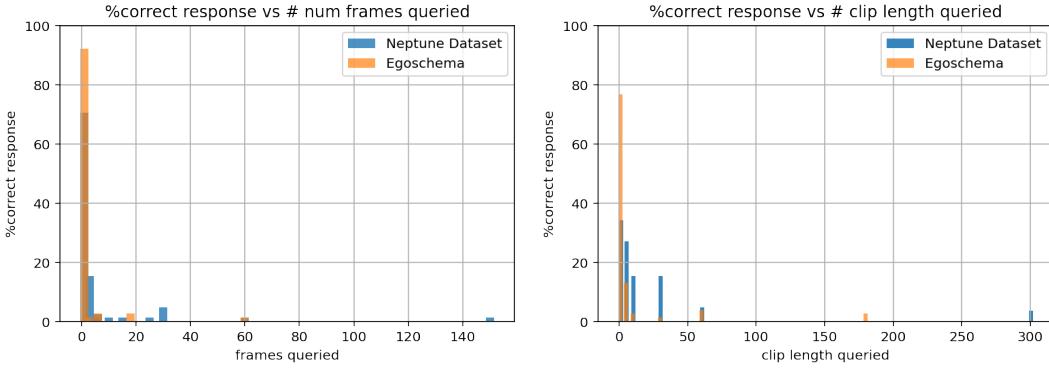


Figure 10: **Model-based Temporal Certificate:** Illustration of video clip querying for the model-based temporal certificate experiment. The red clip is the clip length that resulted in an incorrect response. As we increased the clip length wider, and the model correctly answered the question, we logged the frame count for incorrect response and correct response, and stopped querying. Besides clip length, we vary the fps of the query clip.

Since this experiment queried a set of frames over various clip lengths, we defined it as the “needle in haystack” problem. Here, the needle is defined as a frame or set of frames needed to answer the question correctly, matching a human’s ground truth response, while the haystack is a set of frames which need to be watched to find the needle frames. Iteratively, we increase the video length and fps for the query until the model achieves the correct response.

As shown in Fig. 11, we find that the model needs more frames to answer the question correctly for the Neptune dataset as compared to EgoSchema. This resulted in a mean of 5.39 as certificate frames for Neptune which is 3.37 times the mean certificate frame number of 1.6 for EgoSchema. On the clip length level this translated to a mean of 21.22s of clip needed to respond correctly on the Neptune dataset, whereas for EgoSchema the mean was 9.07s. The model-based certificate lengths turn out to be much smaller than the certificate lengths reported by EgoSchema, where humans needed close to 100s to answer the questions for EgoSchema.

In addition, we define the *effort score* as the fraction of the maximum number of frames needed to be watched before answering the question correctly, as defined in Equation 1. An effort score closer to 0 suggests that the needle isn’t very small compared to the haystack, i.e. most of the frames contain the



Illusionist Josh Norbido attends the grand opening night of Hop & Pickle, a new venue. He waits for guests to arrive, chats with others, and explores the bar. He is seen sitting at the bar with a vodka bottle behind him, looking at signs like "order at the bar" and a McDonald's sign. The modern and stylish decor includes a mix of industrial and rustic elements, creating a warm and inviting atmosphere. The video concludes with him standing in front of an "order at the bar" sign.

A woman expresses frustration with her family for not eating the fresh produce she buys, which often goes bad before they have a chance to consume it. She laments that she buys all this fresh produce, but nobody eats it, and wonders who she is buying it for. She suggests that her husband can use Ashley Madison to find her a new mom who appreciates healthy eating, implying that her current family does not value or consume the fresh produce she buys.

Alex Alfonzo, vice president of Blooms Direct, introduces the video in front of the "Direct Inc. Blooms" sign. He explains that the video will provide instructions on how to care for and arrange roses after receiving them.

answer to the question; while a high effort score means a high percentage of haystack frames needs to be included before we cover all frames required to answer correctly.

$$\text{EFFORT SCORE} = \frac{\text{MAX NUMBER OF FRAMES RESULTING IN AN INCORRECT RESPONSE}}{\text{MIN NUMBER OF FRAMES RESULTING IN A CORRECT RESPONSE}} \quad (1)$$

For Neptune, the mean effort score was 0.47, whereas for EgoSchema, it was 0.19. This suggests that Neptune requires 2.47 times the effort compared to EgoSchema according to the definition above, which closely corroborates the above results for the mean clip lengths needed to solve the questions from the respective datasets.

## F EXAMPLES OF CAPTION QUALITY

We show examples of captions generated by our automatic pipeline in Fig. 12.

## G SOCIETAL IMPACT

Our data may match the distribution of videos and text on the internet. As such, it will mirror known biases on that source of data. For at least this reason, this data set should not be used for training models and is only intended for academic evaluation purposes. To create the dataset, we run large Gemini models, which has a negative externality of energy usage and carbon emissions. For benchmarking, we use existing models. These models are likely to inherit the biases of the data distribution and the pre-trained weights used in their original training.