Language Repository for Long Video Understanding

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Abstract

Language has become a prominent modality in computer vision with the rise of multi-modal LLMs. Despite supporting long context-lengths, their effectiveness in handling long-term information gradually declines with input length. This becomes critical, especially in applications such as long-form video understanding. In this paper, we introduce a Language Repository (`LangRepo`) for LLMs, that maintains concise and structured information as an interpretable (*i.e.*, all-textual) representation. It consists of write and read operations that focus on pruning redundancies in text, and extracting information at various temporal scales. The proposed framework is evaluated on zero-shot video VQA benchmarks, showing state-of-the-art performance at its scale. Our code is available at `github.com/kkahatapitiya/LangRepo`.

1 Introduction

Video data is central to learning systems that can interact and reason about the world. Yet, they also associate with significant challenges such as increased compute requirements and redundant information. This is especially critical in long-form videos. Nevertheless, recent large-language-models (LLMs) [45, 57, 41, 59] have made significant strides in long-video reasoning, thanks to the scale of model/data and large context-lengths that capture long-term dependencies. However, recent studies show that the effectiveness of models declines with longer input sequences [22]. This promotes the search for techniques that effectively utilize the context of LLMs. Moreover, language as a modality has enabled benefits such as rich semantics [48, 27, 15], information sharing among specialized models [58, 25, 10] and interpretability [61, 38], to name a few. Among such, interpretability has a huge societal impact in the age of LLMs, in the context of managing adversities such as bias [24, 8] and hallucinations [60, 6]. Hence, interpretable representations have also been of interest to the community.

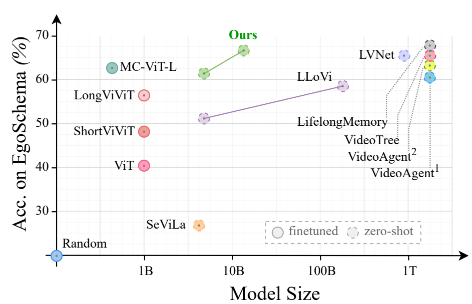

Figure 1: Comparison with prior-art on EgoSchema [26] subset: `LangRepo` outperforms finetuned and zero-shot pipelines of similar scale, while being competitive with pipelines based on much-larger proprietary models. Note that the x-axis is in log-scale.

Motivated by the above, we introduce Language Repository (`LangRepo`), an interpretable representation for LLMs that consists of *all-textual* write and read operations. The write operation (`write-to-repo`) consumes chunks of short-video captions, pruning redundant text and creating concise descriptions that keep the context-utilization of LLMs in-check. Its iterative application with increasingly-longer chunks enables it to learn high-level semantics (*e.g.* long temporal dependencies). The read operation (`read-from-repo`) extracts such stored language information at various temporal scales, together with other optional metadata within the repository entries (*e.g.* timestamps). Altogether, our proposed framework shows state-of-the-art performance on long-video reasoning benchmarks (*e.g.* EgoSchema [26], NExT-QA [52], IntentQA [23]) at its scale, while also being competitive with pipelines based on much-larger proprietary LLMs (see Fig. 1).

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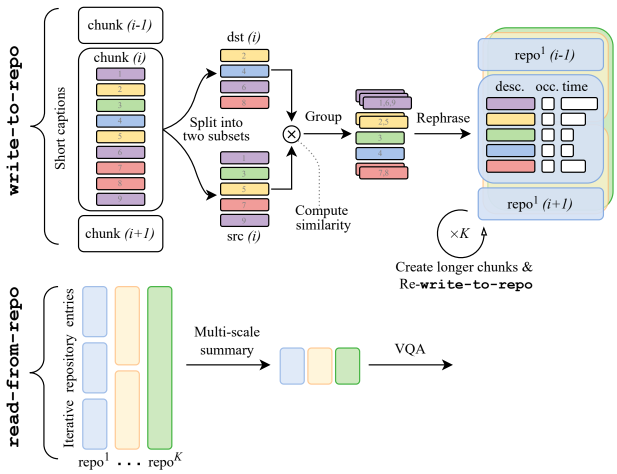

Algorithm Long-video VQA pipeline in `LangRepo`

require captions of video chunks $C^0 = \{c_i^0 \mid i = 1, \cdots, n\}$, number of iterations K.

def `write-to-repo`(c):
  $c_{\text{dst}},\ c_{\text{src}} = \texttt{split}(c)$
  $\text{sim}_{\text{src-dst}} = \texttt{similarity}(\texttt{encode}(c_{\text{src}}),\ \texttt{encode}(c_{\text{dst}}))$
  $c_{\text{grp}} = \texttt{group}(c_{\text{dst}},\ c_{\text{src}},\ \text{sim}_{\text{src-dst}})$
  $c_{\text{reph}} = \texttt{rephrase}(\texttt{template}_{\texttt{reph}}(c_{\text{grp}}))$
  $r = (c_{\text{reph}},\ t,\ o)$ // t: timestamps, o: occurances
  return r

def `read-from-repo`(r):
  $d = \texttt{summarize}(\texttt{template}_{\texttt{sum}}(r))$
  return d

$r_i^0 = \texttt{write-to-repo}(c_i^0)$
$d_i^0 = \texttt{read-from-repo}(r_i^0)$

for k in range(K): // iterative write and read
  $C^{k+1} = \texttt{re-chunk}([\cdots,\ r_i^k,\ \cdots])$
  $r_i^{k+1} = \texttt{write-to-repo}(c_i^{k+1})$
  $d_i^{k+1} = \texttt{read-from-repo}(r_i^{k+1})$

ans $= \texttt{vqa}(q, [\ d_i^0, \cdots])$ // q: query

Figure 2: Overview of Language Repository: `LangRepo` consists of write and read operations. Given short-captions of video chunks, `write-to-repo` prunes redundant captions to generate repository entries by (1) grouping similar captions and (2) rephrasing them, while preserving additional metadata (*e.g*. #occurrences, timestamps). Next, `read-from-repo` generates concise descriptions at different semantic levels by summarizing multi-scale repository entries.

2 Related work

Video models have progressed over the years, going from primitive recognition tasks [39, 18] to complex and fine-grained reasoning tasks over long horizons [37, 56, 11]. More recently, long-video understanding has made a leap forward thanks to benchmark datasets [11, 26, 52] and model improvements [57, 59, 30], showing the importance of modeling long-term interactions. LLMs have further fueled this direction with breakthroughs in caching [9, 19, 16], model-sharding [62, 4, 21] and efficient attention [5, 20]. Even so, maintaining the effectiveness of reasoning over longer inputs is still challenging [22, 53, 36]. This motivates us to think about concise representations that can better-utilize LLM context. Such representations may come in the form of pruning [33, 1], latent memory [34, 12, 51], or external feature banks [50]. However, all these lack interpretability (*i.e*., being able to clearly identify which information gets preserved). Language being a dominant modality [32, 58, 25] that is also interpretable, can be a potential solution to address this limitation. Motivated by these, we introduce an interpretable language representation that can (1) prune redundant information, and (2) extract multi-scale (or, high-level) semantics, enabling better context-utilization in LLMs.

3 Language Repository

We present a Language Repository (`LangRepo`) that iteratively updates with multi-scale information from video chunks. It has multiple advantages including, requiring no training (*i.e*., zero-shot) and being compatible with both LLM-based processing and human interpretation (as it is fully-textual). `LangRepo` consists of two main operations: (1) information writing (`write-to-repo`), which prunes redundancies and iteratively updates language descriptions based on increasingly-longer video chunks, and (2) information reading (`read-from-repo`), which extracts preserved descriptions (together with any optional metadata) in multiple temporal scales. See Fig. 2 (left) for the overall pipeline.

Writing to repository: Our iterative write operation involves two stages: (1) Grouping and (2) Rephrasing redundant text. In the grouping stage, we identify most-similar captions. We first split the captions of each chunk into two sets, namely, source (*src*) and destination (*dst*) captions. Next, we embed all captions using a text-encoder (*e.g*. CLIP [32]), compute cosine similarities between *src-dst* sets, and group most-similar matches together. In the rephrasing stage, each group is rephrased to be a concise and coherent description via an LLM-call, dropping any redundant information. We further preserve additional metadata such as timestamps and #occurrences to avoid any loss of information due to rephrasing. Refer the supplementary for our rephrasing template and a qualitative example. In each subsequent iteration, we re-combine previous repository entries into increasingly-longer chunks with our `re-chunk`(·) operator, and re-write to repository, generating high-level information and forming a multi-scale language representation. See Fig. 2 (right) for the complete algorithm.

Table 1: (Left): Results on EgoSchema [26]. (Right) Results on NExT-QA [52] and IntentQA [23]. We focus on the zero-shot video VQA. `LangRepo` shows a strong performance at its scale. Open-source multi-modal LLMs with video-caption pretraining are de-emphasized for fair comparison.

Model	Params	Subset	Fullset
zero-shot (with proprietary LLMs)			
Vamos [43]	175B	-	41.2
LLoVi [59]	175B	57.6	50.3
ProViQ [3]	175B	-	57.1
MoReVQA [28]	340B	-	51.7
LVNet [31]	<1.8T	66.0	61.1
Vamos [43]	1.8T	-	48.3
VideoAgent[1] [44]	1.8T	60.2	54.1
VideoAgent[2] [7]	1.8T	62.8	-
IG-VLM [17]	1.8T	-	59.8
VideoTree [49]	1.8T	66.2	61.1
LifelongMemory [47]	1.8T	68.0	62.1
zero-shot (with open-source LLMs)			
InternVideo [45]	478M	-	32.1
FrozenBiLM [54]	890M	-	26.9
SeViLA [57]	4B	25.7	22.7
mPLUG-Owl [55]	7B	-	31.1
LLoVi [59]	7B	50.8	33.5
VideoLLaMA 2 [2]	12B	-	53.3
Vamos [43]	13B	-	36.7
InternVideo2 [46]	13B	-	60.2
Tarsier [42]	34B	68.6	61.7
`LangRepo` (ours)	7B	60.8	38.9
`LangRepo` (ours)	12B	66.2	41.2

Model	Params	NExT-QA	IntentQA
zero-shot (with proprietary LLMs)			
ViperGPT [40]	175B	60.0	-
ProViQ [3]	175B	64.6	-
MoReVQA [28]	340B	69.2	-
LVNet [31]	<1.8T	72.9	71.1
IG-VLM [17]	1.8T	68.6	64.2
LLoVi [59]	1.8T	67.7	64.0
TraveLER [35]	1.8T	68.2	-
VideoAgent[1] [44]	1.8T	71.3	-
VideoTree [49]	1.8T	73.5	66.9
zero-shot (with open-source LLMs)			
VFC [29]	164M	51.5	-
InternVideo [45]	478M	49.1	-
SeViLA [57]	4B	63.6	
Mistral [13]	7B	51.1	50.4
LLoVi [59]	7B	54.3	53.6
Tarsier [42]	7B	71.6	-
LLoVi [59]	12B	58.2	56.6
Tarsier [42]	34B	79.2	-
`LangRepo` (ours)	7B	54.6	53.8
`LangRepo` (ours)	12B	60.9	59.1

Reading from repository: As we make a single VQA prediction for a given long-video, our read operation (`read-from-repo`) is applied only after fully-forming the multi-scale repository (*i.e.*, after all write iterations). When reading, we generate summaries for each repo-entry separately via LLM-calls, allowing us to focus on varying temporal spans. Optionally, we can make use of additional metadata by prompting the read operator as "`[timestamps] description (`$\times$`#occurrences)`". Refer the supplementary for our summarizing template. Finally, we concatenate all output descriptions and prompt the LLM again to generate answer predictions.

4 Experiments

In our experiments, we rely on frame or short-clip captions pre-extracted using VLLMs [63, 25], and use open-source LLMs for modeling (*e.g.* Mistral [13] w/ 7B parameters or Mixtral [14] w/ 12B active parameters). We use CLIP-L/14 [32] as the text encoder in similarity-based pruning. In Table 1 (left), we present zero-shot performance of `LangRepo` on standard EgoSchema [26] splits. `LangRepo` shows significantly-better performance at its scale, among models with similar pretraining. On the fullset, we achieve $+10.1\%$ over mPLUG-Owl [55], $+7.7\%$ over LLoVi [59], and $+4.5\%$ over Vamos [43]. On the subset, ours is even competitive with much-larger models based on proprietary LLMs (*e.g.* GPT-4), showing $+6.0\%$ over VideoAgent[1] [44], $+3.4\%$ over VideoAgent[2] [7] and $+0.2\%$ over LVNet [31]. In Table 1 (right), we report zero-shot performance of `LangRepo` on standard NExT-QA [52] validation split and IntentQA [23] test split. On both benchmarks, we outperform models at its scale with similar pretraining (for fair comparison, as our captions have not seen any video pretraining). On NExT-QA, we gain $+9.8\%$ over Mistral [13] and $+2.7\%$ over LLoVi [59]. On IntentQA, `LangRepo` achieves $+8.7\%$ over Mistral [13] and $+2.5\%$ over LLoVi [59]. These results validate the effectiveness of our long-video VQA pipeline. Moreover, in Table 2, we evaluate the founding motivation of this work, showing that `LangRepo` can effectively utilize the LLM context and retain a stable performance over longer input lengths compared to other baselines.

Table 2: While other models drop performance with increasing #captions, `LangRepo` stays more-stable ($1\times$ is 180 captions in [26]).

Model	$0.5\times$	$1\times$	$2\times$
Mistral [13]	49.8	48.8	46.8
LLoVi [59]	57.2	55.4	53.6
`LangRepo` (ours)	56.4	57.8	56.4

5 Conclusion

In this paper, we introduced a Language Repository (`LangRepo`), which reads and writes textual information of long-video chunks, as a concise, multi-scale and interpretable language representation. Both our `write-to-repo` and `read-from-repo` operations are text-based and implemented as calls to a backbone LLM. Our empirical results show a strong performance on multiple VQA benchmarks at comparable settings, while also being (1) less-prone to performance drops at longer input lengths, and (2) interpretable, enabling easier human intervention if and when needed.

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