

ReWind: Understanding Long Videos with Instructed Learnable Memory

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setting

VQA:

dataset: MovieChat-1K dataset (1000 for 9.13min)

1. global : requires processing the entire video and answering questions about its content
2. breakpoint : processing the video up to a specific timestamp and answering questions about the event at that point

metric: acc; score

Temporal Grounding:

dataset: Charades-STA

metric: mIoU; R@XX

motivation

Challenges:

1. self-attention mechanisms require substantial memory that scales quadratically with the number of tokens, making long video processing **computationally intensive**



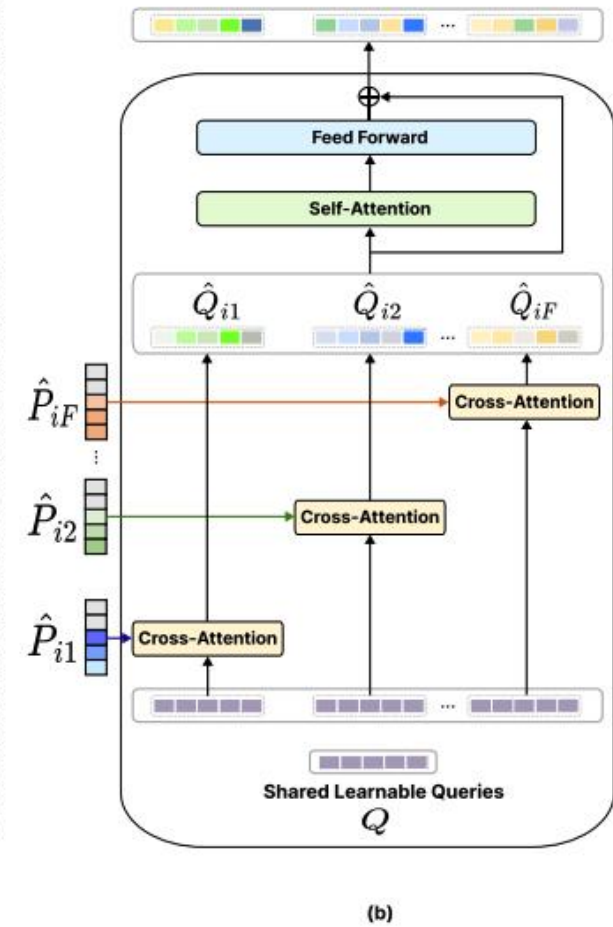
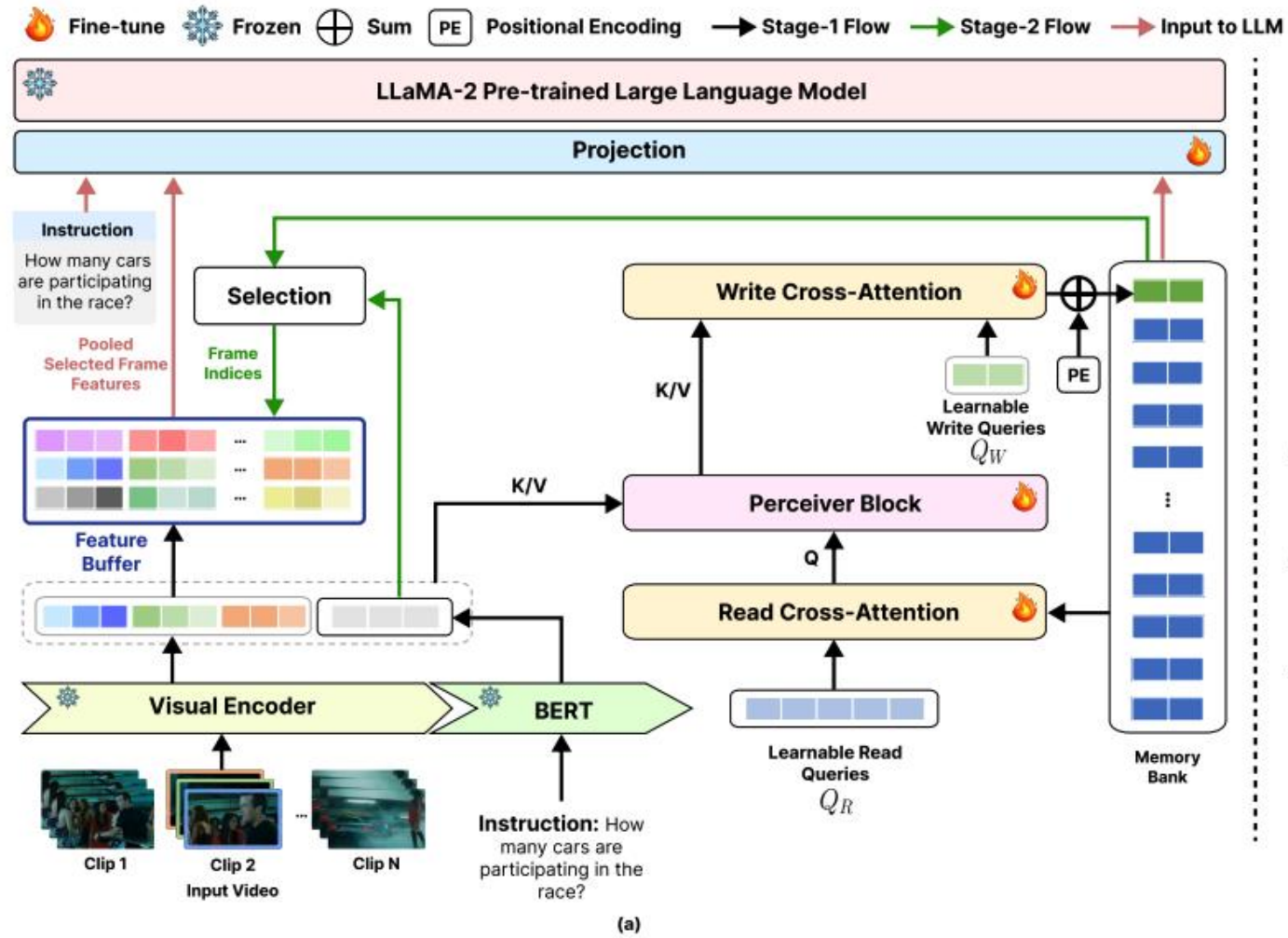
use Q-Former structure to compress spatial information

2. struggle to **effectively model temporal dependencies** over extended sequences



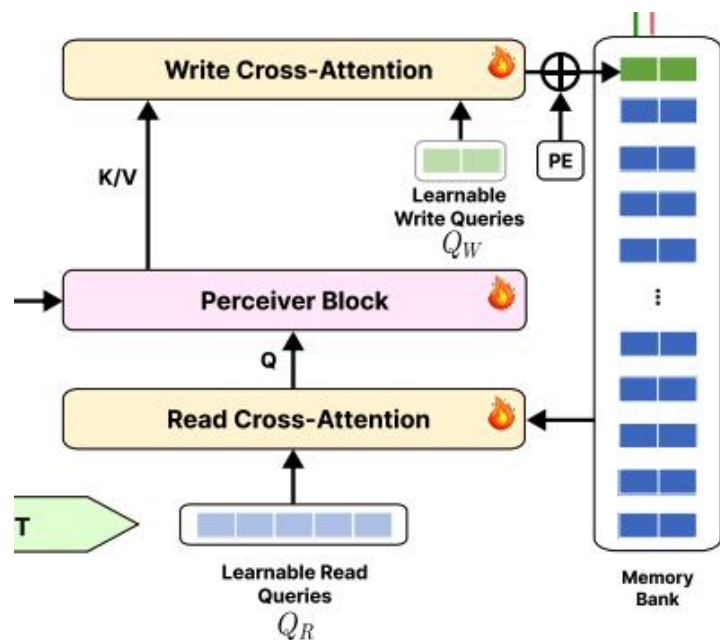
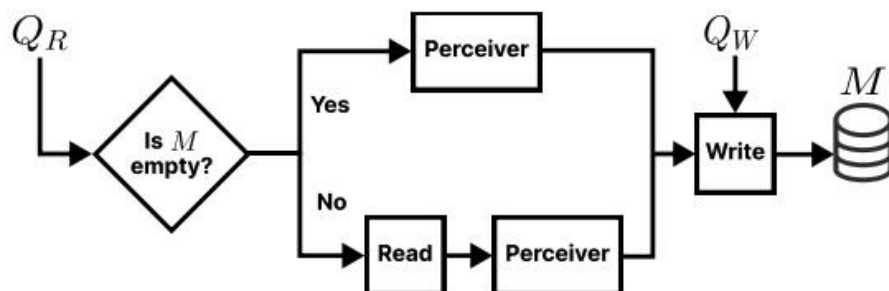
use memory-informed method to preserve temporal fidelity

overview



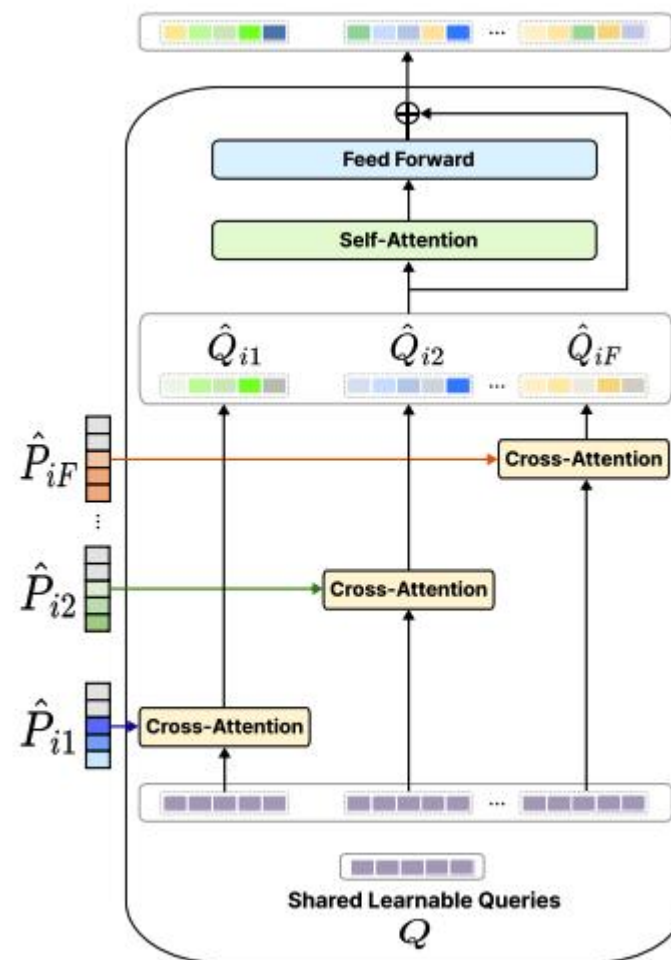
method

Instructed Memory Architecture



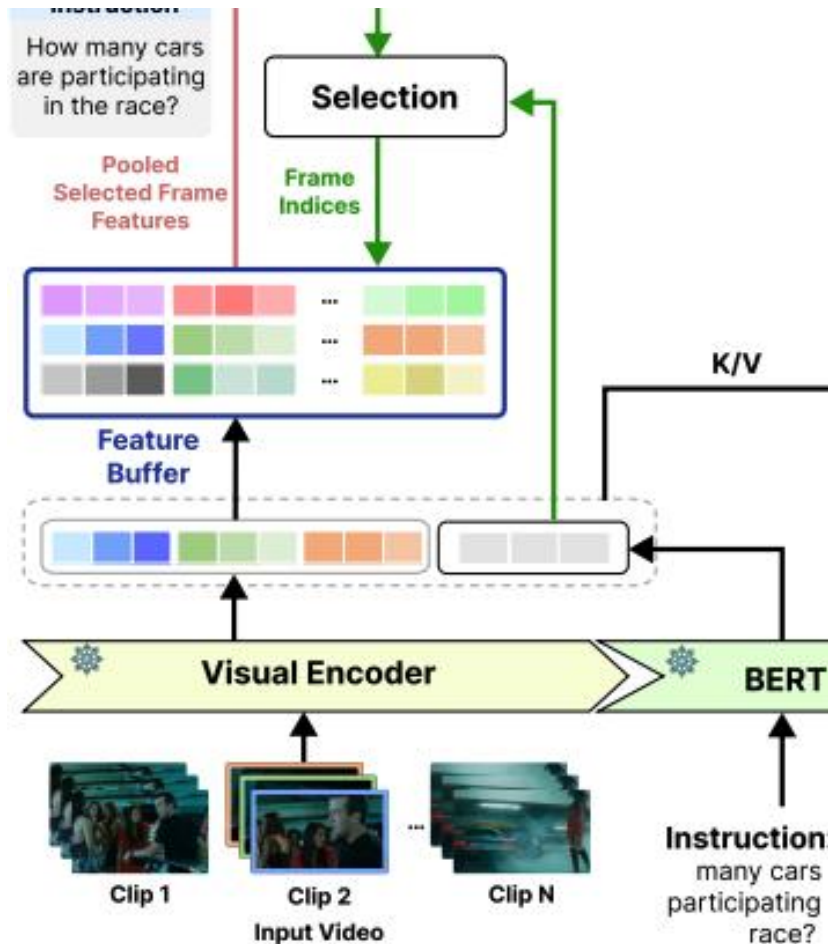
n: How

Perceiver Block



method

Dynamic Frame Selection



1. Instruction based selection
compute the attention matrix between
I and contents of M select top L frames set Z_I
2. Clustering

$$\sigma_l = \exp\left(-\frac{1}{K} \sum_{z_k \in KNN(z_l, Z)} \|z_k - z_l\|^2\right)$$

$$\rho_l = \begin{cases} \min_{j: \sigma_j > \sigma_l} \|z_j - z_l\|^2 & \text{if } \exists j \text{ s.t. } \sigma_j > \sigma_l, \\ \max_j \|z_j - z_l\|^2 & \text{otherwise.} \end{cases}$$

select top K ($\sigma_l \times \rho_l$) frames features Z

final input: $\langle M, \text{spec}, Z \rangle$

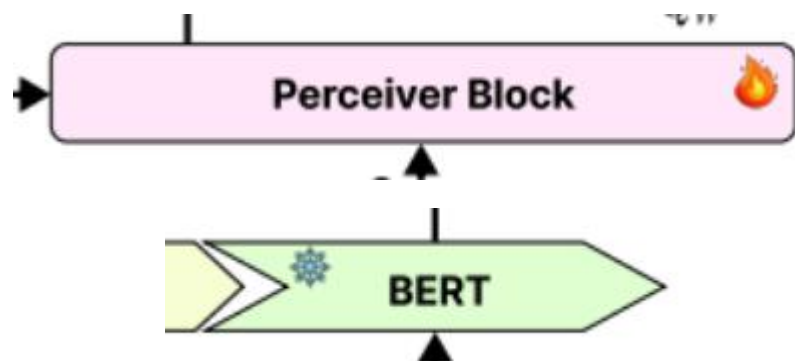
method

Training

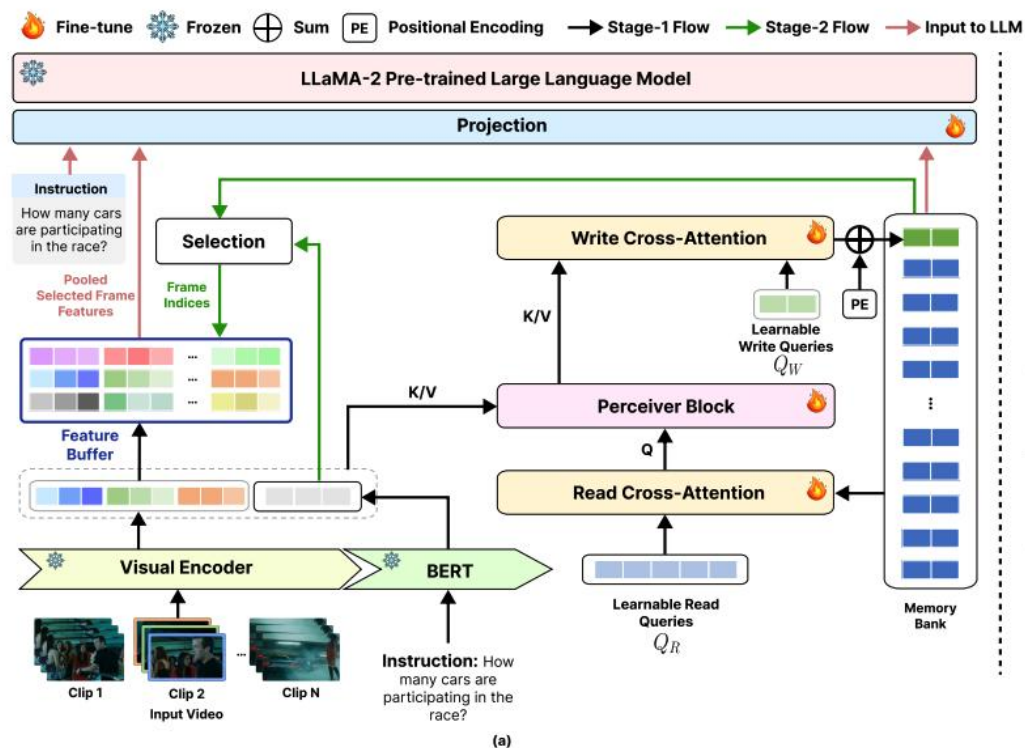
Multimodal Pretraining Stage:
contrastive learn

$$\mathcal{L}_{SigLIP} = -\frac{1}{||\mathcal{B}||} \sum_{i=1}^{|\mathcal{B}|} \sum_{j=1}^{|\mathcal{B}|} \log\left(\frac{1}{1 + \exp(z_{ij}(-t\mathbf{x}_i \cdot \mathbf{y}_j + b))}\right)$$

$\underbrace{\hspace{10em}}_{\mathcal{L}_{ij}}$



Instruction Tuning Stage:



experiment

long video QA

Model	Num Frames	Num Tokens	Global VQA		Breakpoint VQA		Global Generation					Breakpoint Generation				
			Accuracy	Score	Accuracy	Score	CI	DO	CU	TU	CO	CI	DO	CU	TU	CO
Video LLaMA [27]	32	32	51.4	3.10	38.2	2.31	3.30	2.53	3.28	2.77	3.42	2.42	2.85	2.87	2.00	2.87
Video-ChatGPT [18]	100	356	44.2	2.71	49.8	2.71	2.48	2.78	3.03	2.48	2.99	<u>3.11</u>	<u>3.32</u>	3.29	2.62	3.29
Video Chat [14]	32	3072	61.0	3.34	48.3	2.43	3.26	3.20	3.38	2.97	3.47	2.96	3.09	3.24	2.46	3.22
MovieChat [21]	2048	8192	<u>67.8</u>	<u>3.81</u>	<u>50.4</u>	<u>2.96</u>	<u>3.32</u>	<u>3.28</u>	<u>3.44</u>	<u>3.06</u>	<u>3.48</u>	3.07	3.24	<u>3.31</u>	<u>2.70</u>	<u>3.45</u>
ReWind (Ours)	548*	1184*	80.6	4.46	57.2	3.4	4.18	4.00	4.24	4.02	3.54	3.41	3.37	3.64	2.97	3.61

short video QA

Model	LLM	Backbone	CI	DO	CU	TU	CO	AVG
Video Chat [14]	Vicuna-7B	ViT-G	2.23	2.50	2.53	1.94	2.24	2.29
Video LLaMA [27]	Vicuna-7B	ViT-G	1.96	2.18	2.16	1.82	1.79	1.98
Video-ChatGPT [18]	Vicuna-7B	ViT-L	2.40	2.52	2.62	1.98	2.37	2.38
LLaMA Adapter [28]	LLaMA-7B	ViT-L	2.03	2.32	2.30	1.98	2.15	2.16
Chat-UniVi [12]	Vicuna1.5-7B	ViT-L	2.89	2.91	<u>3.46</u>	2.39	2.81	<u>2.89</u>
VTimeLLM [11]	Vicuna1.5-7B	ViT-L	2.78	3.10	3.40	<u>2.49</u>	2.47	2.85
MovieChat [21]	LLaMA2-7B	ViT-G	2.76	2.93	3.01	2.24	2.42	2.67
LLaMA-VID [15]	Vicuna-7B	ViT-G	2.96	<u>3.00</u>	3.53	2.46	2.51	<u>2.89</u>
ReWind (Ours)	LLaMA2-7B	ViT-G	<u>2.91</u>	2.85	3.42	2.71	<u>2.68</u>	2.91

Temporal grounding

Model	Charades-STA			
	R@0.3	R@0.5	R@0.7	mIoU
Video Chat [14]	9.0	3.3	1.3	6.5
Video LLaMA [27]	10.4	3.8	0.9	7.1
Video-ChatGPT [18]	20.0	7.7	1.7	13.7
GroundingGPT [16]	-	29.6	11.9	-
TimeChat [20]	-	32.2	13.4	-
VTimeLLM [11]	<u>51.0</u>	<u>27.5</u>	<u>11.4</u>	<u>31.2</u>
ReWind (Ours)	59.0	41.6	20.53	39.3

AdaCM²: On Understanding Extremely Long-Term Video with Adaptive Cross-Modality Memory Reduction

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setting

Long-Term Video Understanding

dataset: LVU

content understanding and metadata prediction tasks

Video Captioning:

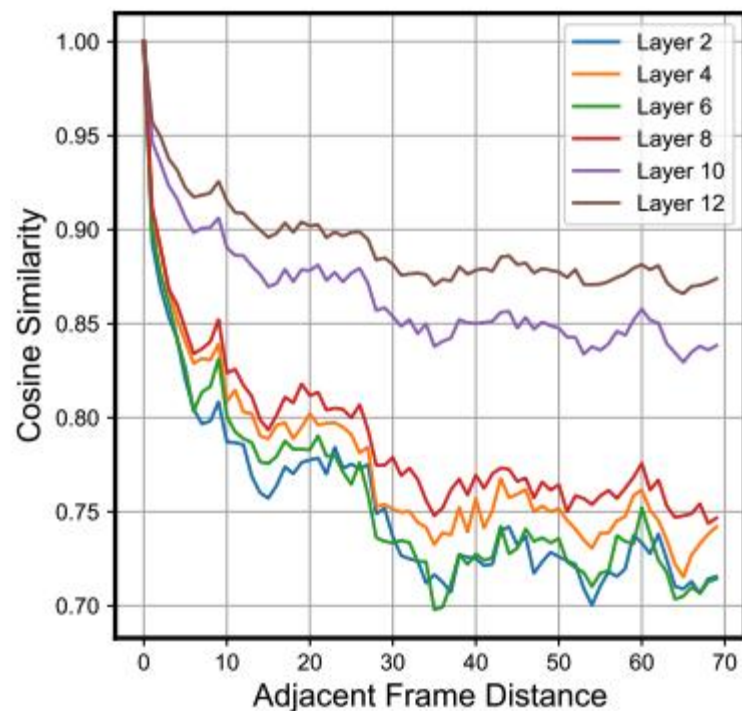
dataset: MSRVT; MSVD; YouCook2

metric: METEOR“语义正确性” / CIDEr“表述符合共识”

motivation

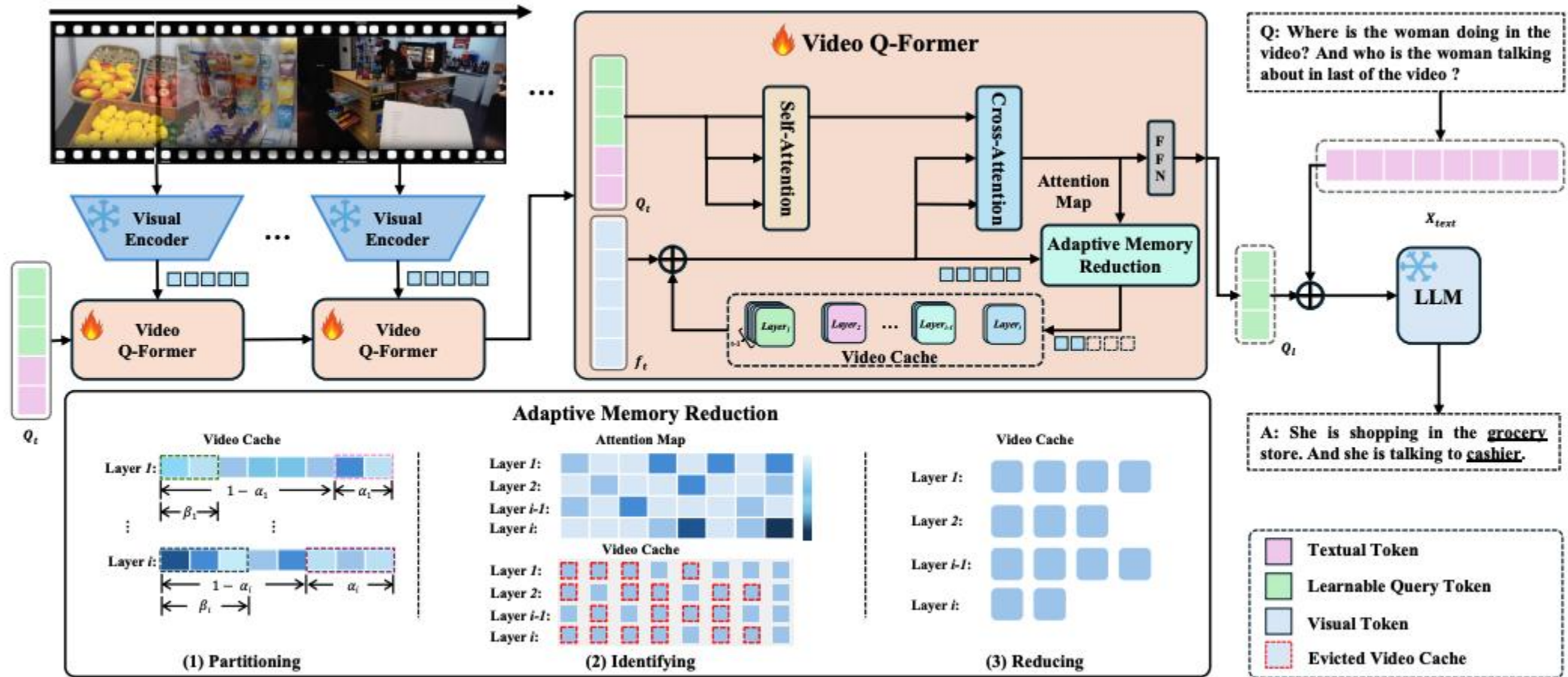
Observation

1. Only a subset of visual tokens exhibits high correlations to the text query within a frame
2. Correlation varies across different layers



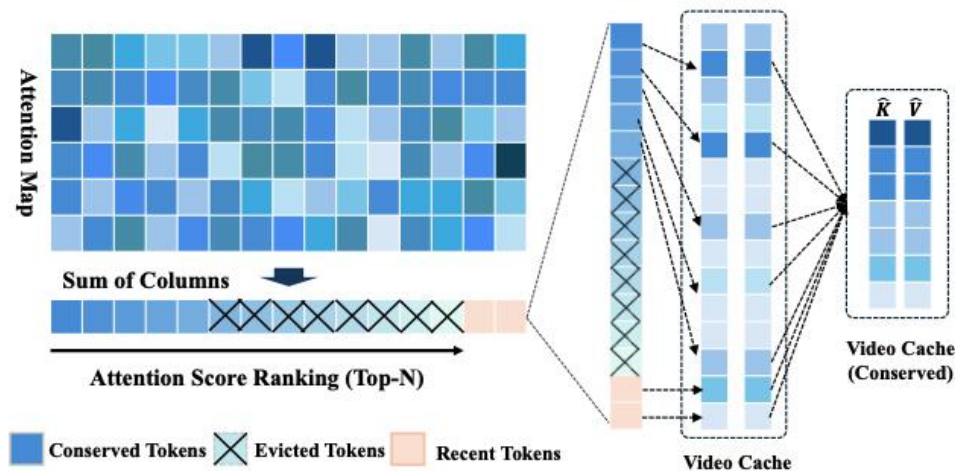
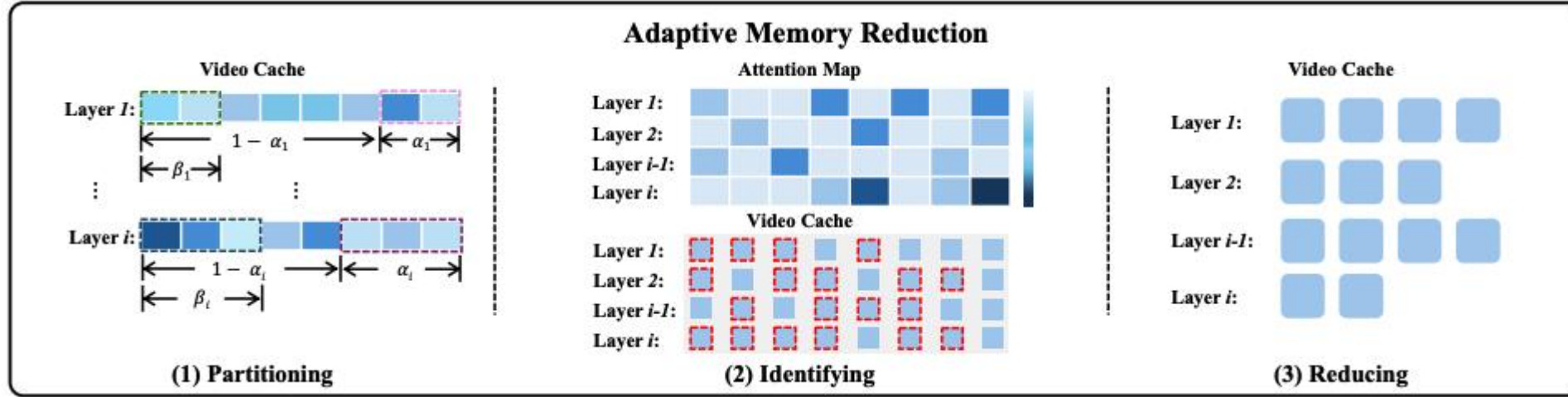
Adaptive Memory Reduction with
Cross-Modality Attention

overview



method

Adaptive Memory Reduction with CrossModality Attention



Algorithm 1 Layer-wise Adaptive Video Reduction.

- 1: **Input:** Video frames $\{f_t\}_{t=1}^T$, hyper-parameters α, β for each layer;
- 2: **Output:** Reduced video KV cache K_t, V_t .
- 3: **for** $t = 1$ to T **do**
- 4: $K_t \leftarrow [K_{t-1}, f_t W_K]; V_t \leftarrow [V_{t-1}, f_t W_V];$
- 5: **Partitioning:** $K_t \rightarrow [\hat{K}_t, \tilde{K}_t]; V_t \rightarrow [\hat{V}_t, \tilde{V}_t];$
- 6: **Identifying:** Determine S_t^c using Eq.5;
- 7: **Reducing:** Obtain $\bar{K}_t$ using Eq.7;
- 8: $K_t \leftarrow [\bar{K}_t, \tilde{K}_t]; V_t \leftarrow [\bar{V}_t, \tilde{V}_t];$
- 9: **end for**

experiment

Table 1. Comparison with state-of-the-art methods on the LVU dataset. The underlined number means the second best.

Model	Content			Metadata				Avg
	Relation	Speak	Scene	Director	Genre	Writer	Year	
Obj_T4mer [45]	54.8	33.2	52.9	47.7	52.7	36.3	37.8	45.1
Performer [9]	50.0	38.8	60.5	58.9	49.5	48.2	41.3	49.6
Orthoformer [32]	50.0	38.3	66.3	55.1	55.8	47.0	43.4	50.8
VideoBERT [36]	52.8	37.9	54.9	47.3	51.9	38.5	36.1	45.6
LST [19]	52.5	37.3	62.8	56.1	52.7	42.3	39.2	49.0
VIS4mer [19]	57.1	40.8	67.4	62.6	54.7	48.8	44.8	53.7
S5 [43]	67.1	<u>42.1</u>	73.5	67.3	<u>65.4</u>	51.3	48.0	59.2
MA-LMM [16]	58.2	44.8	<u>80.3</u>	<u>74.6</u>	61.0	<u>70.4</u>	<u>51.9</u>	<u>63.0</u>
Ours	<u>63.1</u>	40.2	86.2	75.4	68.0	77.0	62.5	67.5

Model	Breakfast	COIN
TSN [44]	-	73.4
VideoGraph [18]	69.5	-
Timeception [17]	71.3	-
GHRM [13]	75.5	-
D-Sprv. [25]	89.9	90.0
ViS4mer [19]	88.2	88.4
S5 [43]	90.7	90.8
MA-LMM [16]	<u>93.0</u>	<u>93.2</u>
Ours	94.4	93.3

Model	MSRVTT		MSVD		YouCook2	
	M	C	M	C	M	C
UniVL [28]	28.2	49.9	29.3	52.8	-	127.0
SwinBERT [24]	29.9	53.8	41.3	120.6	15.6	109.0
GIT [41]	32.9	73.9	<u>51.1</u>	<u>180.2</u>	<u>17.3</u>	<u>129.8</u>
mPLUG-2 [47]	34.9	80.3	48.4	165.8	-	-
VideoCoca [49]	-	73.2	-	-	-	128.0
VideoLLaMA [52]	32.9	71.6	49.8	175.3	16.5	123.7
MA-LMM [16]	<u>33.4</u>	<u>74.6</u>	51.0	179.1	17.6	131.2
Ours	33.0	73.1	51.4	189.4	17.6	125.6